DISSERTATION

PHARMACEUTICALS, PHYSICIANS AND MONEY

Submitted by

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ABSTRACT

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Pharmaceutical companies have contributed tremendously to improving health and quality of life. Treatments unavailable decades ago now extend lives and eliminate the need for invasive medical procedures. New cures are developed every year through research and development. Pharmaceutical companies typically face high failure rates while investing in research and development, the size of which may reach as high as 2.56 billion dollars (Kakkar, 2015). To increase returns from the products that are finally in the market, pharmaceutical companies engage in medical marketing. Medical marketing, and particularly promotions to physicians, come with a hefty cost to a final consumer. Numerous studies have found associations between promotional payments and brand name prescribing (Yeh et al., 2016; Perlis and Perlis, 2016), even if equivalent low-priced products are available (Akande and Aderibigbe, 2007; Taylor et al., 2016).

This dissertation explores pharmaceutical industry-physician relationships and examines the factors influencing the size and frequency of promotional payments to physicians. The dissertation also studies the behavior of physicians and considers why some physicians accept more in payments than others.

Chapter one examines the behavior of pharmaceutical companies, the patterns of competition surrounding patent expiration, the generic entry, and the choice of promotional instruments. It discusses the strategies employed by pharmaceutical companies in their efforts to keep competition away from the market and enjoy longer periods of monopoly or duopoly

power. The study argues that patent expiration and subsequent entry of generic competitors are strong predictors of promotional payments. Also, pharmaceutical companies drastically change the size and frequency of payments after FDA approval of new dosages or new uses of an existing drug for the purposes of shifting the market away from the generic competition and increasing revenues. Finally, the chapter discusses the issues surrounding the information and persuasion debate, showing that promotional payments serve both purposes.

Chapter two examines the role of cultural norms and the regulatory environment in the acceptance of pharmaceutical promotional payments by foreign-trained internal medicine doctors. It shows that the home country's corruption norms and the host country's regulatory environment are both important predictors of corrupt behavior among foreign-trained physicians. In the absence of rules and regulations, physicians from different countries adopt somewhat similar behavior. However, the propensity to accept promotional payments decreases among physicians from less corrupt countries when a host country's regulatory environment restricts acceptance of such payments. The study also finds a strong relationship between tenure, physician gender, and propensity to accept promotional payments. It suggests considering different norms and cultural backgrounds when designing and integrating ethical training in the residency and fellowship curricula. It also recommends adopting more stringent conflict of interest policies in hospitals.

Chapter three analyzes the relationship between medical school policies and the propensity of promotional payment acceptance later in a physician's career. It shows that some medical school policies affect the likelihood and the size of accepted promotional payment and

interactions with the pharmaceutical representatives later in a physician's career. Restrictive medical school meal policies seem to be especially effective in reducing interactions and acceptance of food and beverage-related payments. The study also finds a strong relationship between tenure, physician gender, physician practice size, and propensity to accept promotional payments. It suggests adopting stringent medical school policies to influence payment acceptance behavior later in physicians' careers.

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CHAPTER 1: STRATEGIES AND PROMOTIONS TO PHYSICIANS

1.1 Introduction

Drugs, that were not available decades ago, are now an essential part of everyday life. The development of new drugs through research and development (R&D) is fraught with immense risk and high expenditures. The R&D productivity of the pharmaceutical industry has been declining continuously over the last decade, accompanied by increasing costs of bringing a new drug to market and delay of drug approval processes by government agencies (Pammolli, Magazzini and Riccaboni, 2011). To encourage investments and competition based on innovation, the intellectual property system is designed to grant the innovators monopoly rights for a period of time. However, the declining productivity and rising costs of R&D are forcing companies to adopt new systems to introduce innovative products to market and to focus on strategies that extend an existing product's lifecycle (Song and Han, 2016).

To increase the returns from existing products, pharmaceutical companies practice methods such as reformulating existing molecules and combining drugs (Chandon, 2004), introducing and obtaining exclusivity based on new uses and dosages of an existing drug. These strategies aim to extend a drug's protection period and, therefore, high revenues. Pharmaceutical companies also heavily promote drugs to physicians in their efforts to increase revenues and develop brand loyalty. A critical feature of the demand for prescription drugs is that the end consumer, the patient, does not select the drug he or she will consume (Scott Morton, 2000). Physicians, instead, choose treatments and therefore drugs for final consumers. To maintain the market and extract large profits, brand-name drug producers widely use physician promotion tools. Numerous studies have found associations between promotional payments and brand-name

prescribing (Yeh et al., 2016; Perlis and Perlis, 2016), even if equivalent low-priced products are available (Akande and Aderibigbe, 2007; Taylor et al., 2016).

Promotions and other strategies employed by pharmaceutical companies to prolong a drug's lifecycle and thus high revenues come with a hefty cost to a final consumer. To hold pharmaceutical companies and physicians accountable, the Physician Payments Sunshine Act (PPSA), also known as section 6002 of the Affordable Care Act (ACA) of 2010, was passed, requiring medical product manufacturers to disclose to the Centers for Medicare and Medicaid Services (CMS) any payments or other transfers of value made to physicians or teaching hospitals (Department of Health and Human Services, 2013). Using various types of promotional payments for 712 brand-name drugs over 5 years, this chapter examines strategies employed by pharmaceutical companies in their efforts to keep competition away from the market, prolong drugs' lifecycles and enjoy larger profits. The study considers if new dosages or new uses of a drug were FDA approved during the period of observation. It shows that pharmaceutical companies heavily promote the new uses and new dosages of an existing drug in their efforts to shift the market from existing versions of the drug and increase revenues. The chapter also investigates the patterns of promotion surrounding patent expiration and generic entry, demonstrating that payments decline with each additional generic competitor's entry to the market. Finally, the study investigates the information versus persuasion debate, showing that physician payments serve both purposes.

To my knowledge, no previously published study has used as comprehensive list of drugs and detailed information to examine the strategic behavior of pharmaceutical companies. This study is unique in its attempt to assess the strategy of introduction of new uses or dosages of an existing drug to the market across many drugs. The findings contribute to growing evidence of

the pharmaceutical companies' efforts to prolong drug's lifecycle. They may serve as a guide for policymakers in their efforts to improve existing laws and target certain types of interactions between the pharmaceutical industry and providers.

The remainder of the chapter is laid out as follows: Section 1.2 details the strategies and promotional instruments used by the pharmaceutical industry. A summary of the data is found in Section 1.3, empirical methods and results are presented in Section 1.4 and the chapter closes with concluding remarks.

1.2 The Strategies and Promotional Instruments

Developing a new, potentially life-saving drug is an extraordinarily expensive, time-consuming, and risky endeavor (Taylor, 2015). Therefore, not all pharmaceutical companies invest in the development of drugs. Pioneer pharmaceutical companies that develop new drugs and bring them to market are called *brand-name drug producers*. They typically invest heavily in R&D. The size of R&D-related expenditures per new drug may reach as much as 2.56 billion dollars (Kakkar, 2015). It takes on average of fourteen years in the United States to develop a new drug, obtain approval and bring the drug to market. Only 8 percent of drugs for which an Investigational New Drug Application (INDA) is filed eventually receive approval from the Food and Drug Administration (FDA) for marketing (Sloan and Hsieh, 2012). Thus, it is crucial for pharmaceutical companies to recoup investments and extract high profits once the drug is in the market.

In the last few decades, pharmaceutical companies have been struggling to develop and market products that are effective enough to compete with existing products and meet regulatory

requirements (Mittra and Tait, 2012). Decreased productivity of R&D and generic competition have caused brand-name drug producers to deploy a range of strategic approaches (Paul et al., 2010), such as extending the patent protection period by introducing new dosages and new uses of an existing drug, obtaining exclusivity rights, undermining generic competition and/or striking deals with generic producers (Feldman and Frondorf, 2017). Such strategies aim to maximize profits.

Three pillars of brand-name drug's profitability are patent protection, pricing, and promotional activities. Patent protection includes patents, orphan, pediatric and product exclusivities, as well as other tools and strategies that extend exclusive production period and avoid direct competition. The exclusive production enables brand-name drug producers to charge higher than competitive prices (Congressional Research Service, 2020), and practice price differentiation (Feldman, 2018). Promotional activities, meanwhile, include promotions to prescribers and hospitals, final consumers (patients) and government agencies. This chapter explores patents and promotions to prescribers and hospitals.

1.2.1 Extending Patent Protection and Drug's Lifecycle

Brand-name drugs are typically protected by several patents. A patent is an exclusive right that grants pharmaceutical manufacturers monopoly power on their new products for a fixed period, allowing them to exclude others from making, using, or selling the invention to recoup their investments (Gubby, 2019). Without patent rights many innovations in areas such as isolation and purification of proteins, DNA sequences, monoclonal antibodies, gene expression systems would have never occurred (Cockburn, 2004).

The patent for a prescription drug is typically awarded for twenty years in the United States. To assess a drug's safety and efficacy, the company applies for a patent long before the clinical trial. Therefore, the effective patent period after the drug has finally received approval by FDA is often around seven to twelve years (Folland, Goodman and Stano, 2010).

Whether society grants intellectual property in the form of a patent or exclusivity (will be discussed later in this part), the system is designed in such way that competitors, i.e., generic producers, may enter the market and drive prices down after a patent protection or exclusivity period expires (Feldman, 2018). Brand-name drug companies face a drastic decline in market share and price once generics enter the market. The immediate decline in revenue after patent expiration is referred in literature as the "patent cliff" (Jimenez, 2012). For instance, GlaxoSmithKline's antiulcer drug Zantac lost 60 percent of its U.S. market share within four months of its patent expiry (Harrison, 2004).

The temptation to avoid the impact of the patent cliff is strong when even a few months of additional monopoly profits can be worth hundreds of millions of dollars or more (Feldman and Frondorf, 2017). Brand-name drug companies can employ a range of strategies to maximize patent protection, extend a drug's lifecycle and retain its market share and high profits. A good example is Cephalon's Provigil that was set to lose its secondary patent in 2015. Due to the narrowness of Provigil's secondary patent, the generic drug producers planned to enter the market in 2006. Cephalon settled its patent lawsuits with generic producers, paying them more than 200 million dollars to delay market entry until 2012 (Congressional Research Service, 2020). From 2004 to 2009, pharmaceutical companies filed a total of 218 final settlement agreements involving brand and generic drug producers. 66 of those settlements involved compensation to the generic drug producers (pay-for-delay) combined with a delay in generic

entry (Federal Trade Commission, 2010). Large pharmaceutical companies often engage in dealmaking to realign their portfolios (Bansal, Backer and Ranade, 2018) and push the patent cliff as far away as possible (Feldman and Frondorf, 2017). Another strategy employed by brand-name drug producers for the purposes of extending drug's lifecycle and extracting monopoly profits is mergers and acquisitions. In the first half of 2018 alone, there were 212 mergers and acquisitions in the industry, exceeding combined value of 200 billion dollars (Bansal, Backer and Ranade, 2018).

This paper discusses strategic behavior of pharmaceutical companies surrounding a drug's entry to the market, patent expiration, entry of generic competition as well as approval of new uses and dosages of a drug. The paper limits the discussion of pharmaceutical strategies only to those that can be examined through the lens of physician promotions. Strategies, such as pay-for-delay, mergers, acquisitions, using restricted distribution systems[1], REMS-based[2] (Risk Evaluation and Mitigation Strategy) strategies are left out of discussion.

When a drug's patents or exclusivities expire or are found invalid, in theory, anyone who can obtain FDA approval becomes eligible to sell the medication, and thus generic competition begins. A *generic producer*, according to Hatch-Waxman Act, can submit Abbreviated New Drug Applications (ANDA) to the FDA and does not have to go through lengthy approval processes as does a brand-name drug producer (Feldman and Frondorf, 2017). To prolong the effective patent life for the drug beyond the expiry date of the patent, brand-name drug producers can take various pathways in different stages of the product's lifecycle (Chandon, 2004).

[1] Restricted or controlled distribution systems are mandated by the FDA as part of safety protocols when a drug presents special concerns regarding safety, administration, or storage.

[2] REMS is a risk management and safety plan that the FDA can require of a pharmaceutical company to implement beyond the standard labeling requirements that apply to most drugs.

Determining which pathway to pursue depends on a company's capabilities, priorities, and the chosen time period. Not all options are available at a given time.

Pharmaceutical companies can use the strategies of changing the formulations, dosage schedules and producing combinations of drugs to switch the market to a slightly different product. A good example of such strategies in use is Namenda, the blockbuster dementia medication, that was scheduled to lose patent protection in 2015. The company launched a longer-acting version of the original drug product and began encouraging patients and doctors to switch to the patent-protected, longer-acting version to undermine generic competition (Feldman and Frondorf, 2017).

Brand-name drug producers may also seek exclusivities, such as orphan drug exclusivity, new patient population exclusivity, and new product exclusivity, to block generic competition from entry. Even if a patent of the drug is expired, being covered by any of those exclusivities, allows a brand-name producer to block the competition for a period:

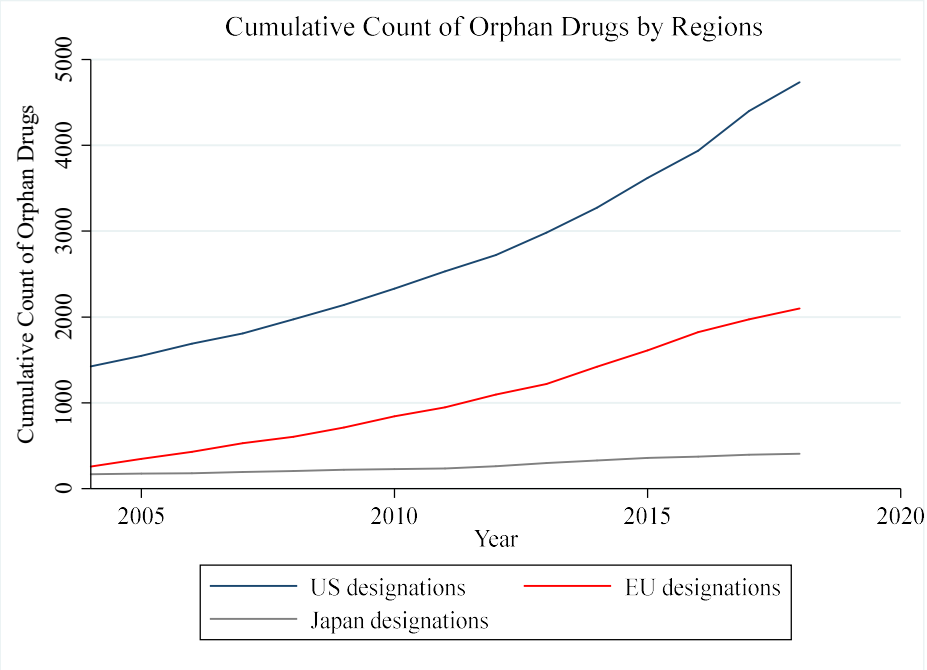
- ***Orphan drug exclusivity is a 7-year exclusivity*** granted to drugs that are approved and designated specifically to treat diseases and conditions affecting populations of 200,000 individuals or fewer (source: Food and Drug Administration). There are approximately 7,000 rare, mostly life-threatening or life-limiting diseases. Treatments are available for just 5 percent of them (QuintilesIMS Institute, 2017). Due to concerns about insufficiency of investments for the development of treatments for small patient populations, the Orphan Drug Act was passed in 1983 and amended through the Hatch-Waxman Act in 1984. Orphan Drug Act was designed to encourage and protect investments in neglected fields of medicine (Feldman, 2018). Today, orphan drugs account for a substantial part of drugs approved by the FDA (figure 1.1).

- ***Pediatric exclusivity*** extends exclusive marketing (or period of patent protection) by 6 months.
- ***Product exclusivity*** is awarded for new clinical studies and lasts for 3 years. New uses of the drug, effects and accompanying symptoms that were not manifested during the clinical study and not familiar at the time of registration, become clear during clinical use (post-FDA approval). If new indications appear to be promising, an extension of the drug approval may be requested (Bhat, 2005).

A drug does not actually have to be newly developed to qualify for orphan drug, pediatric, or product exclusivity. One-third of orphan drugs approved since 1983 were repurposed mass market drugs or drugs that received multiple orphan approvals (Tribble and Lupkin, 2017). A good example is AstraZeneca's Crestor, a cholesterol-lowering statin, which received an Orphan Drug Designation in 2014. The studies found that Crestor could be used for the treatment of pediatric homozygous familial hypercholesterolemia ("pediatric HoFN"), a rare genetic disorder that heightens cholesterol levels and can cause premature death. Notably, AstraZeneca simply found that Crestor, a cholesterol lowering drug, could reduce cholesterol among those with HoFN, which could then mitigate the effects of the disease. As it is often the case, the study of HoFN started only years after the drug was first approved and was granted supplementary 7 year exclusivity, nearly a month before generics would have otherwise entered the market (Feldman and Frondorf, 2017).

In the U.S., the number of orphan drugs has been climbing steadily since 1983. There were 5,792 orphan drug designation requests from 1983–2016, ranging from 16 in 1983 to 472 in 2015. In 2016, 36 percent of novel drug approvals were orphan drugs with 449 approved orphan

therapies for 549 orphan indications (QuintilesIMS Institute, 2017). This exceeds the European Union's and Japan's novel orphan drug approvals combined.



Source: EvaluatePharma (2019)

Figure 1.1: Cumulative count of Orphan drug designation by regions

As was discussed earlier, when a drug's patents or exclusivities expire or are found invalid, generic competition may begin. It has been estimated that prices can drop as much as 20 percent when the first generic enters the market. With multiple generics, prices may eventually drop by 80–85 percent (Caves, Whinston and Hurwitz, 1991). Meanwhile, the first generic to successfully challenge a drug patent or the application of that patent is the only generic allowed in the market for 6 months (Paragraph IV challenge under Hatch-Waxman Act). During this 6-

month period, a duopoly market exists, in which the only players are the brand-name company and the first generic competitor (Feldman, 2018). The caveat here is that the 6-month period of duopoly production does not need to start right away, leaving room for deals between brand-name and generic producers.

Pharmaceutical companies may also strike licensing deals, "authorized generic" agreements permitting the generic company to manufacture and/or sell the brand-name formulation as a generic without filing for generic approval, with profit sharing or royalty deals attached (Feldman and Frondorf, 2017). Brand-name drug producers can even produce their own "branded-generics". Such strategies allow a brand-name drug producer to hold on to a portion of the profits that would otherwise go to the first generic entrant. Such strategies can deter generic entry in small markets (Song and Han, 2016).

1.2.2 Promotions to Prescribers and Sunshine Act

The second pillar of brand-name drug's profitability is promotion. The World Health Organization defines drug promotion as, "all informational and persuasive activities by manufacturers and distributors, the effect of which is to induce the prescription, supply, purchase and use of medicinal drugs" (World Health Organization, 1998). Each year, physicians in the United States alone write more than three billion prescriptions, or about twelve prescriptions per American (Weiss, 2010). Finding communication channels to promote drugs to prescribers and hospitals is crucial to ensure higher returns on investment especially when a drug is protected by a patent(s).

Pharmaceutical companies use a variety of promotional tools including provision of food and beverage, distribution of gifts and free samples, hiring of physicians to consult or speak on

behalf of their products and funding of organizations that provide continuing medical education. Over the course of the last few decades, pharmaceutical companies have spent more on prescriber (physician) promotions than they have spent on research or consumer advertising (Schwartz and Woloshin, 2019). On average, physicians in the U.S. meet with pharmaceutical sales representatives four times a month (Weiss, 2010). Campbell et al. (2007) reveal that the vast majority of physicians (94 percent) report some type of relationship with the pharmaceutical industry, and most of these relationships involve receiving food in the workplace (83 percent) or receiving drug samples (78 percent). Visits and gifts from pharmaceutical representatives tend to increase prescription sales for specific products and lead to low-quality prescribing behavior (Mintzes et al., 2013). Drug promotion can create "artificial" product differentiation (Leffler, 1981), resulting in use of high-priced, heavily promoted brand-name products (Yeh et al., 2016; Perlis and Perlis, 2016). A study of 667,278 physicians prescribing to Medicare Part D beneficiaries found that receiving any payment from the pharmaceutical industry was associated with increased odds of prescribing drugs of uncertain medical benefit (Sharma et al., 2018). DeJong et al. (2016) showed that receiving a single meal from a pharmaceutical sales representative was associated with an increased rate of prescribing promoted brand-name medication to Medicare patients.

An example of promotional payments altering physician's prescribing behavior and dangers associated with it is the case involving the aggressive push of fentanyl spray. Insys Therapeutics was accused of paying millions in drug promotions encouraging physicians to prescribe a highly addictive fentanyl spray. Promotional payments aimed at physicians in the form of speaker fees and educational opportunities helped to boost sales for poorly justified prescriptions that were really meant for cancer patients in severe pain and costing as much as

19,000 dollars a month (Richer, 2019). Another example of negative outcomes due to promotions comes from Merck's highly promoted drug Vioxx that was withdrawn from the market in 2004. Although Merck was well-aware of Vioxx's fatal outcomes, it continued to aggressively promote the drug to physicians (Berenson, Harris and Meier, 2004), causing approximately 140,000 heart attacks and an estimated 60,000 deaths (Graham et al., 2005).

As medical marketing increasingly received public attention, many doctors and other professionals called for additional regulation of medical marketing. These concerns prompted legislative responses at both the state and federal levels, aiming to limit the influence of provider-targeted pharmaceutical marketing (Weiss, 2010). Eventually similar provisions became part of the Affordable Care Act. The Physician Payment Sunshine Act, also known as section 6002 of the Affordable Care Act of 2010, requires pharmaceutical companies to report to the Secretary of Health and Human Services any payment or transfer of value to providers (with some exceptions) or any financial conflict of interest (Diaz, 2011). The Federal Government collects and publishes information about the payments that drug and device companies make to prescribers and teaching hospitals for things like travel, research, gifts, speaking fees, and meals.

Using various types of promotional payments for 712 brand-name drugs over 5 years (2014-2018), this paper analyzes the size and frequency of promotional payments surrounding market entry, patent expiration and subsequent generic entry in pharmaceutical markets. It also considers the choice of promotional tools by pharmaceutical companies and some strategies pharmaceutical companies adopt at different points of a drug's lifecycle. Typically, studies use specific drug examples to discuss pharmaceutical company strategies. Instead, this chapter examines the market of drugs and analyzes pharmaceutical companies' preferred strategies using wide-scale evidence from promotions to prescribers and teaching hospitals. In the following

sections, I discuss the unique data mobilized to address research questions, the empirical model deployed, and various tests designed to evaluate the promotions by pharmaceutical companies.

1.3 Data

Much of the work done to date on financial relationships and conflicts of interest has lacked context on the type and scope of interactions between prescribers and pharmaceutical companies. I use both total payments and total number of interactions with prescribers and teaching hospitals per drug and per year as well as payments and interactions across various promotional channels to analyze the strategic behavior of pharmaceutical companies. The Open Payments 2014-2018 database is utilized for the purposes of this study. It contains 39 million unique entries with detailed information on the date and size of the payment to each physician and hospital, the nature of the payment (e.g., food, speaker fees, travel, etc.) and the name of the associated drug or device. The sample is limited to promotional payments in the United States. The database reflects payments for those drugs, biological products and devices that are: a) reimbursed by Medicare, Medicaid, or Children's Health Insurance Program; b) require a prescription (or doctor's authorization) to administer; c) require premarket approval or premarket notification by the FDA[3] (Centers for Medicare and Medicaid Services, 2021). For the purposes of this study, I chose promotional payments for brand-name drugs only. Payments related to royalties, ownership, dividends, and charity are excluded from the sample because of their non-marketing nature[4]. Drug samples are also not included in the study, because the Open Payments database

[3] This applies to devices and medical supplies.

[4] The unit of analysis is a drug. The payments made to physicians and hospitals are aggregated by a drug.

does not record samples of drugs provided to prescribers by pharmaceutical sales representatives. Also, materials distributed during medical meetings and conferences may also be fully or partially absent from the database. Although the definition of gifts is broad[5] and could include materials distributed during medical meetings and conferences, there is no general guidance with regards to recording distributed materials to prescribers (physicians) and teaching hospitals during such meetings (see Nature of Payment, Centers for Medicare and Medicaid Services).

The Open Payments 2014-2018 database had thousands of recorded devices, biologics, and drugs. By characteristics, devices vastly differ from drugs and have a different approval process. Thus, they were excluded from the sample. Biologics were also excluded from the sample. Due to the complexity of their structures and manufacturing, producing generic versions of biologics, called biosimilars, is extremely difficult and, often, absent for most biologics (Makurvet, 2021). Additionally, the approval processes of generic version for biologics differs from those for chemical drugs (source: Biosimilar Development, Review, and Approval). After carefully investigating and correcting mistakes in spelling of drug names, excluding devices and biologics, the sample was decreased to 1293 drugs. Further investigation of the data allowed to exclude drugs that were recalled from the market during the period of observation, decreasing the sample to 1187 drugs. 60 percent of the remaining sample was randomly chosen (712 brand-name drugs) to obtain additional information and conduct the study.

Because the paper focuses on advertising behavior of the time-limited monopolies (brand-name drugs), it is important that drugs included in the sample have unambiguous dates of patent expiration, generic entry and FDA approval dates. Brand-name drug producers often obtain tens of patents to protect their monopoly power. However, each drug is typically protected by one

[5] Gifts are promotional items that have the company's name printed on them. "Gifts are a general category which includes anything a company provides to a physician or teaching hospital that does not fit into another category" (source: Nature of Payments, Centers for Medicare and Medicaid Services).

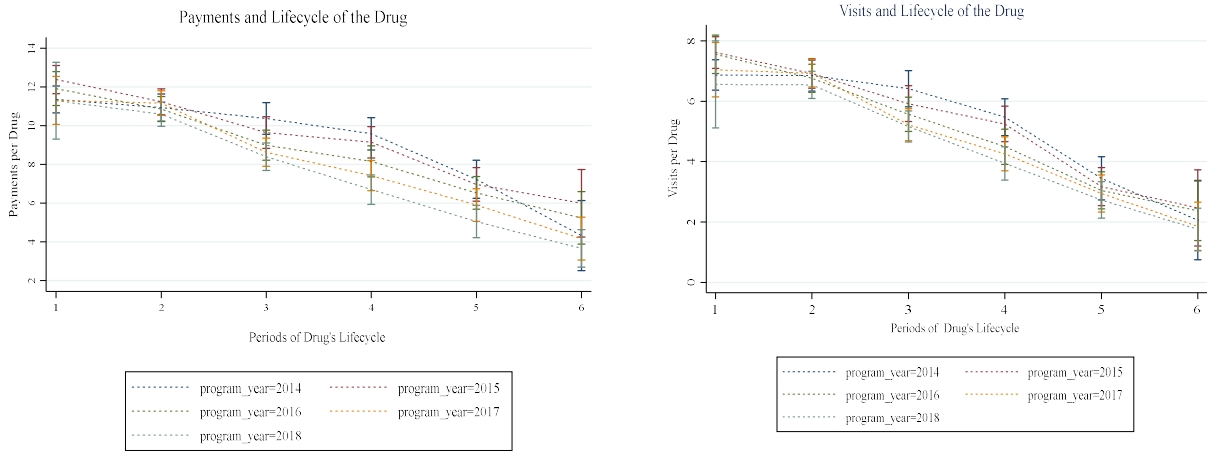
main patent (or exclusivity) that prevents competitors from producing the same content and chemical structure. I hand-collected the information for all 712 brand-name drugs, their unique patent expiration[6] (i.e., year of patent expiration) or exclusivity, patent extension applications and lawsuits, FDA approval dates, FDA approval dates for new uses and dosages of the drug, generic alternative availability, FDA approval dates of generic substitutes, the number of generic substitutes as well as use and therapeutic classes of drugs from sources such as FDA Orange book, drugs.com, U.S. Patent and Trademark Office, a brand-name drug companies' 10-k's and various articles about lawsuits and deals.

The Open Payments database includes only the dates and positive values of payments to prescribers. When no payment is made in a certain year by a pharmaceutical company for a drug, a zero payment does not appear in the database. If the chapter used the database as is, without making corrections for zero payments, the study would run the risk of overestimating the effects of entry to the market, patent expiration and generic entry. Therefore, zero payments were added to the data for those cases when no payments were made by pharmaceutical companies in a particular year.

The size and frequency of payments may change depending on how long the drug has been in the market. The use of promotional instruments may also vary throughout a drug's lifecycle. I develop the lifecycle of a drug variable to account for time (in years) since market entry. As can be seen in figure 1.2, both the average size and frequency of promotional payments tend to decline over the duration of drug's lifecycle.

[6] If a manufacturer was granted an extension of drug's main patent by the court, the new (extended) date was considered as a patent expiration date.

Payments and Lifecycle of the Drug	Frequency of Payments and Lifecycle of the Drug



Note: Periods are determined by the following: first two years of operating in market is *period 1*; 3 to 6 years in market is *period 2*; 7 to 10 years in the market (when some drugs are set to face patent expiry) is *period 3*; 11 to 15 years of operating in the market is *period 4*; 16 to 20 is *period 5*; and 21 to 37 is *period 6*.

Figure 1.2: Payments and frequency of interactions by periods of drug's lifecycle

The study is concerned only with brand-name drug producers and their competitive behavior. As was discussed earlier in the chapter, brand-name drugs are typically protected by several patents, allowing pharmaceutical companies to exclude others from the market, recoup their investments and extract monopoly profits. Finding communication channels to promote drugs is crucial to ensure higher returns on investment especially while a drug is protected by a patent(s). This is perhaps why only 133 out of 712 drugs in the database used for this study lost their patents prior to the period of observation (55 of those 133 drugs lost their patents up to two years prior to period of observation). 166 drugs were set to lose their patents during the period of observation and 413 drugs were set to lose their patents only after the period of observation. The majority of promoted drugs were still protected by patents and enjoyed market monopoly.

Instead of creating new drugs, pharmaceutical companies are often recycling and repurposing old ones (Feldman, 2018). The strategies employed by brand-name drug producers

may involve developing new formulations, dosage schedules, or combinations to obtain new patents (known as *product hop*). Indeed, 78 percent of the drugs associated with new patents are not new drugs, but existing ones (Feldman, 2018). While attempting to switch to new formulations, brand-name producers usually provide incentives to various participants in the payment and reimbursement chain, including insurers, managed care organizations and pharmaceutical benefit managers to catalyze a product hop (Feldman and Frondorf, 2017). The brand-name company can divide the market, with some patients moving to the new version for which no generic is available and advertise extensively, pressure doctors to write prescriptions with terms such as "Dispense as Written" or "Brand Medically Necessary". To complete the product hop, brand-name companies can eventually discontinue the previous version of the drug (Feldman and Frondorf, 2017). The sample used in this chapter consists of novel drugs that were in the market as of 2020. Additionally, I consider new uses of a drug and account for exclusivities obtained for a drug's new uses, since pharmaceutical companies may change promotion behavior when introducing new uses and/or dosages of drugs.

At or around a drug's patent expiration, the generic drug producer submits an Abbreviated New Drug Application (ANDA) to the FDA, demonstrating that the generic product is "bioequivalent" to the brand-name product (source: FDA)[7]. Automatic substitution laws, known as state "drug product selection" (DPS) laws, exist in all fifty states allowing substitution of a generic for a branded drug when available (Chressanthis, Dahan and Fandl, 2015).

With the entry of generic alternative, the price and market share (thus, the revenue) of the brand-name drug quickly shrinks (Caves, Whinston and Hurwitz, 1991). Therefore, from investment perspective, a more reasonable strategy would be promoting the drug while it enjoys

[7] In addition to expiry of valid patents, generic companies may start a battle with brand-name producers over patents of questionable validity months or years before the patent expiration date.

a market monopoly. It is hardly surprising that the majority of drugs in the sample did not have generic alternatives during the period of observation.

During the period of patent protection, only one firm produces a drug based on a specific set of chemical ingredients. While such patent protection is a source of market power, it is incorrect to infer that the patent holder necessarily is the only producer in the market. The reason is that, in general, a particular disease (such as diabetes or depression) can be treated with various drugs that differ in precise chemical composition but have similar therapeutic properties (Sloan and Hsieh, 2012). Inclusion of classification or number of brand-name substitutes is important in terms of analyzing advertising behavior in crowded and not so crowded markets. Iizuka (2004) shows that as the number of competitors increases, firms advertise less, leading it to suggest the existence of a free-riding problem. Meanwhile, in the case of monopolistic competition, when drug producers face many competitors, differentiation of products (drugs) that are less than perfect substitutes and advertising is important in increasing sales and thus profits (Lacy and Martin, 2004). Since prescribers (physicians) select the treatments and therefore drugs for the end consumer (patient) (Scott Morton, 2000), one would expect more aggressive promotions by brand-name drug producers to prescribers for the purpose of standing out from competition and increasing sales.

As a proxy for close substitute availability, I use a detailed classification approach. All 712 brand-name drugs are grouped into 203 therapeutic classes of drugs and used in some of the regressions as a proxy for therapeutic substitutes. It is important to note that the study does not include sales volumes for each drug. Along with the hardship of obtaining such data, it also may raise an endogeneity issue related to promotions increasing volume of sales, which can lead to increased promotional expenditures itself.

Table 1.1: Descriptive statistics, all payments

	Size of Payments		Frequency of Payments		
	Mean	Standard Deviation	Mean	Standard Deviation	N
Payments	11 987.81	70 758.25	144.03	718.76	192 240
Non-expired patent	17 090.47	85 604.93	203.15	859.92	126 954
Expired patent	2 231.56	19 313.53	31.65	262.40	59 940
No generic alternative	15 956.06	84 106.65	190.87	858.55	125 388
Drug has a generic alternative	4 922.52	33 659.54	61.03	314.45	61 506
Drug has 0- 2 generic alternatives	14 302.97	77 292.07	172.09	784.88	159 570
Drug has 3-5 generic alternatives	1 614.75	19 422.9	19.55	161.47	10 260
Drug has 6-8 generic alternatives	238.58	4 557.82	1.94	17.36	5 886
Drug has 9 or more generic alternatives	283.29	3 478.22	1.34	17.96	11 178
New uses/dosages approved 2013-2018	33 552.14	13 4730.2	351.79	1 187.05	14 364
No new uses/dosages approved 2013-2018	10 557.7	63 421.15	131.19	673.75	172 530
Lifecycle of drug:					
0-2 years in the market	24 802.43	99 948.99	241.12	921.34	26 298
3-6 years in the market	21 648.44	108 062	231.62	966.08	49 788
7-10 years in the market	8 738.58	42 623.52	142.48	691.75	36 234
11-15 years in the market	5 517.59	28 586.99	102.07	528.42	33 588
16-20 years in the market	2 112.78	16 463.49	40.25	293.41	27 972
21 and more years in the market	946.59	11 422.17	7.49	66.82	13 014

The effectiveness of different promotional tools or communication channels to promote new and mature drugs may differ (McGettigan et al., 2000), but pharmaceutical companies benefit from a variety of promotional channels to market their drug and reach their target markets (De Laat, Windmeijer and Douven, 2002). A careful investigation of the data shows that pharmaceutical companies tend to rely heavily on certain promotional channels such as speaker fees, travel and lodging, food and beverage and consulting. Speaker fees constitute the biggest portion of a pharmaceutical companies' promotional budget (52 percent), followed by food and beverage (21 percent), consulting (13 percent) and travel and lodging (9 percent). However,

those are not the types of payments pharmaceutical companies use most frequently. In 92 percent cases, pharmaceutical companies use food and beverage payments to reach out to healthcare providers and potentially influence their prescribing behavior.

Promotional budget allocation and type of payments often depend on a product's lifecycle (De Laat, Windmeijer and Douven, 2002), competition, and patent expiration. While table 1.1 presents statistics of the data that combines all types of payments, table 1.2 details the frequency and the size of transactions by nature of payments.

Table 1.2: Descriptive statistics, nature of payments

	Size of Payments (in 1000)		Frequency of Payments (visits in 1000)		
	Mean	Standard Deviation	Mean	Standard Deviation	N
Speaker Fees	5 862.42	41 768.34	2.86	19.46	192 240
Consulting Fees	1 489.77	30 500.15	0.72	8.92	192 240
Food and Beverage Payments	2 314.79	12 711.07	125.29	665.18	192 240
Educational Payments	87.66	1 294.43	3.03	39.97	192 240
Travel and Lodging	1 037.04	5 917.83	3.59	21.19	192 240
Honoraria	184.93	3 080.17	0.10	1.77	192 240
Grants	50.31	3 632.53	0.01	0.15	192 240
Gift and Entertainment	2.91	242.16	0.17	9.75	192 240
Space Rental (in hospitals)	104.07	1 084.08	0.08	0.85	192 240

Finally, the chapter studies promotional payments by states[8]. Few states either banned gifts to prescribers or required prescribers to disclose gifts they received from pharmaceutical companies prior to the adoption of the Sunshine Act. I consider such geographic variation to examine the relationship between gift regulations, disclosure policies, and promotional payments.

[8] States, D.C. and U.S. territories as Puerto Rico, Guam and Virgin Islands

1.4 Empirical Strategy and Results

The primary empirical strategy exploits the differences in promotional expenditures by drug's lifecycle, patent expiration, availability of a generic alternative(s) and whether the drug had FDA approved new uses or dosages during the period of observation. One of the challenges associated with estimating such relationships is a large mass point at zero and positive values, as shown in figure 1.3.

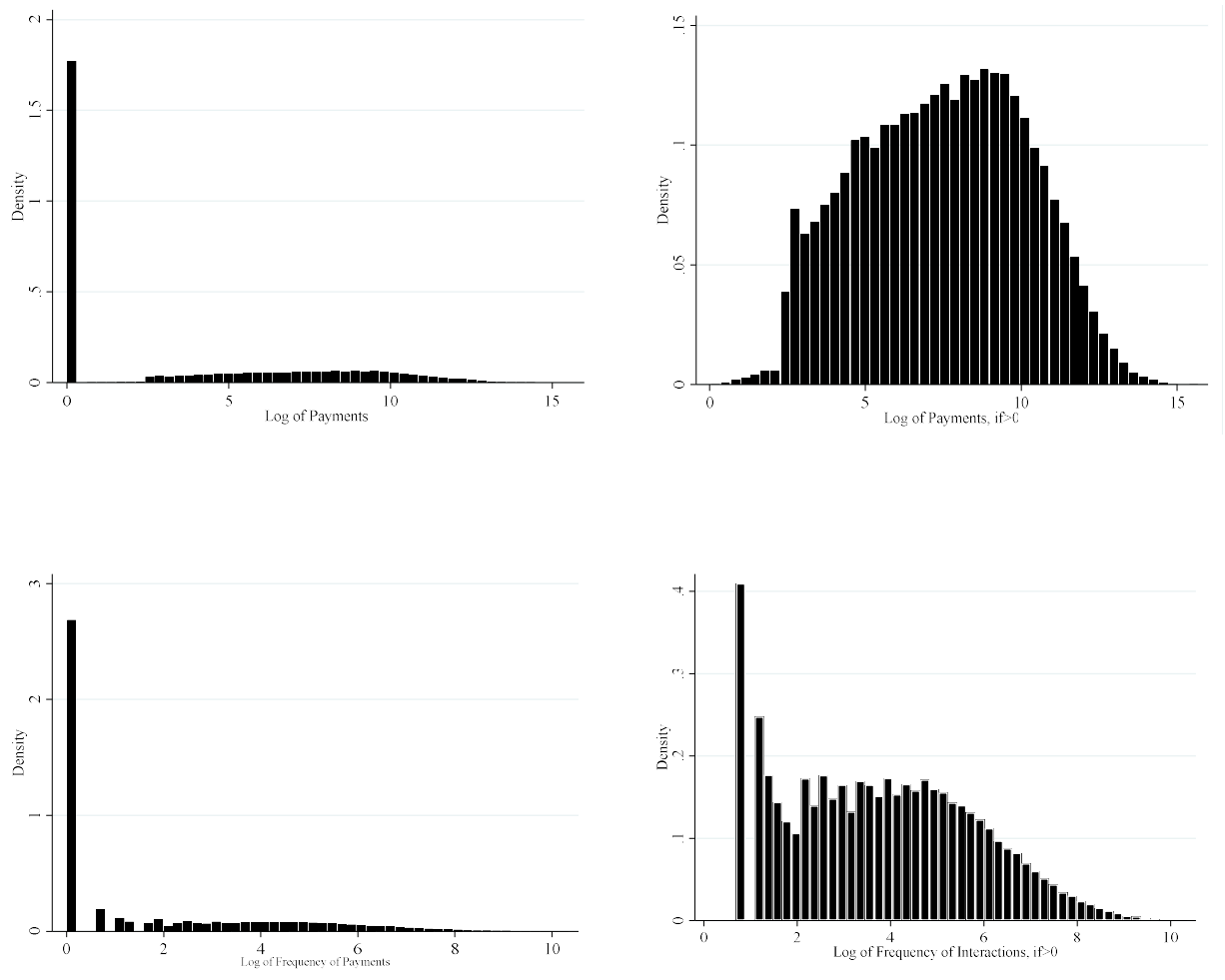


Figure 1.3: The size and frequency of payments

The Physician Payments Sunshine Act, as was discussed earlier in this chapter, requires pharmaceutical companies and medical device manufacturers to disclose to the Centers for Medicare and Medicaid Services (CMS) any payment or transfers of value made to prescribers or teaching hospitals. Zeros in the data reflect no transaction or no payment rather than representing a missing value[9]. In recent decades, the health economics literature has been increasingly using the two-part model as the best way to model a dependent variable with a large mass at zero and many positive values (Belotti et al., 2015, Cawley and Meyerhoefer, 2012; Lê Cook et al., 2010; Mihaylova et al., 2011; Deb and Norton, 2018). This model has a commonly used counterpart for count data called the "hurdle" model (Cameron and Trivedi, 2013; Jones, 1989). As in Belotti et al. (2015), this chapter uses the term "two-part" model, describing models which include different equations for the mass point and the continuous part of the dependent variable. The equation for the mass point estimates the probability of being at the mass point (have a zero outcome). Then, conditional on a positive outcome, an equation for the positive outcome is modeled (Belotti et al., 2015).

Letting $f_{positive}$ be the conditional density of y when $y > 0$, the probability distribution of y can be written as:

$$g(y|x) = \begin{cases} \{1 - \Pr(y > 0|x)\} & if\ y = 0 \\ \Pr(y > 0|x) * f_{positive}(y|y > 0, x) & if\ y > 0 \end{cases} \qquad (1.1)$$

[9] Tobit model is not a good fit for the data used in this chapter. A single mechanism in Tobit models determines being at the mass point or having a positive value (Wooldridge, 2010). The Heckman selection model (Heckman,1979) is not a good fit in this context either since zeros are not missing values. Also figure 1.3 shows a gap between mass point at zero and positive values, making the Heckman selection model less appropriate (Greene, 2012).

This definition is general and does not require or imply any relationship between $\Pr(y > 0|x)$ and $f_{positive}$. It is important to note that there is no independence requirement between the stochastic elements in the equations for the mass point and the continuous part of the dependent variable (Deb, Norton and Manning, 2017). The parameters of this model are estimated in two steps: the parameters of the model for $\Pr(y > 0|x)$ are estimated separately from the parameters of the model for $f_{positive}(y|y > 0, x)$.

There are two main issues which must be addressed in two-part models. The first involves modeling the mass point. The choice is typically between Logit and Probit models[10]. The second issue concerns modeling the continuous portion of the dependent variable. The choice of the model depends on the characteristics of the dependent variable. Many outcome variables in health economics and biostatistics are characterized by heteroscedasticity, heavy skewness in the right tail, and kurtotic distributions, rendering OLS on the raw scale of dependent variable inapplicable. Econometricians have historically relied on logarithmic or other transformations of dependent variable, followed by regression of the transformed dependent variable on independent variables using OLS, to overcome problems of heteroscedasticity, severe skewness, and kurtosis (Box and Cox, 1964). However, the true form of heteroscedasticity is rarely known, and any retransformation can potentially yield biased estimators unless considerable effort is devoted to studying the specific form of heteroscedasticity (Basu and Rathouz, 2005). To avoid such problems of retransformation, biostatisticians and economists have focused on the use of generalized linear models (GLMs) with quasi-likelihood estimation (Wedderburn, 1974). GLMs offer a range of alternative functional forms to match the relationship between the expected value of the dependent variable

[10] Logit model was arbitrarily chosen as is typically done in health economics research that utilizes two-part models. If instead, a probit model was chosen, the results in terms of predicted values and marginal effects would be virtually identical as noted in Deb, Norton and Manning (2017) and Norton and Dowd (2017).

and the linear index of covariates (Deb, Norton and Manning, 2017). GLM generalizes the ordinary linear regression model by allowing the expectation of the outcome variable to be a function (known as the link function) of the linear index of covariates, not simply the linear function of the index. In addition, GLMs also explicitly model the heteroskedasticity (Belotti et al., 2015). I use the GLM framework to model $(y|y > 0, x)$.

Specification Tests for GLM

I use a Box-Cox test to determine what power function will transform the dependent variable, total payments, to be closest to symmetric. The Box-Cox test is limited to observations with positive values. Deb, Norton and Manning (2017) explain that the Box-Cox approach tests which scalar power, δ, of the dependent variable, y^{δ}, results in the most symmetric distribution. A power of $\delta = 1$ corresponds to a linear model, $\delta = 0.5$ to the square root transformation, and $\delta \to 0$ to the natural log transformation model (Deb, Norton and Manning, 2017). The estimated coefficient for the data is close to zero (δ =0.06) corresponding to the natural log transformation.

Next, I performed the modified Park test (Park, 1966) to determine the distribution family, that is, the relationship between the mean and the variance. Deb, Norton and Manning (2017) argue that the Gaussian distribution in the GLM should be used when the coefficient on the expected value is close to 0 because the variance is unrelated to the mean. Poisson-type distribution should be used when the coefficient is close to 1, the Gamma distribution when the coefficient is close to 2 and the inverse-Gaussian distribution when the coefficient is close to 3. The estimated coefficient of 2.2 for the data leads to the choice of gamma link. In summary, the specification tests supported the use of the log link and the gamma distribution.

As figure 1.3 shows, frequency of payments may also be treated as continuous variable. Tests to determine power and link functions for dependent variable frequency of payments was conducted in the same fashion. The estimated coefficient for Box-Cox test is close to zero (δ =0.008) corresponding to the natural log transformation. Meanwhile, the coefficient for modified Park test was 2.17, supporting the use of the Gamma distribution. Therefore, both size of payments and frequency of payments (interactions) regressions utilize two-part model, with Logit model in the first part and GLM model with log link and the gamma distribution in the second part.

Model specification

In the main econometric specification, the dependent variable is total payments per drug (i) per state (j). In some regressions, however, frequency of payments per drug per state is used as a dependent variable. The first part of the model examines the likelihood of promotional payment on the availability of generic competition, patent expiration, lifecycle of the drug, FDA approved new uses or dosages and other characteristics.

$$\Pr(TotalPayments_{ij} > 0) = \nu_0 + \nu_1 NonexpiredPatent_i + \nu_2 GenericAvailability_i + \nu_3 NewUsesorDosages_i + \nu_4 StatePolicies_j + \nu_5 Lifecycle_i + \nu_6 YearFixedEffects_{ij} + \nu_7 ClassificationFixedEffects_i \quad (1.2)$$

Where, $NonexpiredPatent_i$ is a dummy variable revealing whether brand-name drug i is still protected by a patent(s). $GenericAvailability_i$ is a dummy variable that indicates the availability of at least one generic competitor for brand-name drug i in the period of interest.

Alternatively, in some regressions I use the actual number of generic competitors each year. $NewUsesorDosages_i$ indicates whether drug i had new FDA approved uses or dosages during the period of interest. $StatePolicies_j$ is a dummy variable examining whether payments made for drug i are in the state j that adopted gift regulations and disclosure policies prior to the Sunshine Act. Finally, $Lifecycle_i$ indicates how long brand-name drug i has been in the market (in years).

The second part of the model examines the size of the payments (positive payments) using the variables explained above. The equation of interest in a simplified form is the following:

$$\mathrm{E}(\mathrm{Log}(TotalPayments_{ij}) \mid TotalPayments_{ij} > 0) = g^{-1}(\beta_0 + \beta_1 NonexpiredPatent_i + \beta_2 GenericAvailability_i + \beta_3 NewUsesorDosages_i + \beta_4 StatePolicies_j + \beta_5 Lifecycle_i + \beta_6 YearFixedEffects_{ij} + \beta_7 ClassificationFixedEffects_i) \quad (1.3)$$

Where g^{-1} is the link function in the GLM model. It is important to note that the two-part model does not make any assumption about the correlation between the errors of equations (1.2) and (1.3). The errors do not need to be independent to get consistent estimates of the parameters ν and β (Belotti et al., 2015). Finally, the overall mean can be written as the product of expectations from the first and second parts of the model (Belotti et al., 2015), as follows:

$$\mathrm{E}(y|x) = \Pr(y > 0|x) \times \mathrm{E}(y|y > 0, x).$$

Results by Drug, State and Year

In the analyses presented below both size of payments (total payments) and frequency of payments were used as dependent variables. The fixed effects include year effects and therapeutic classification effects. Robust standard errors are clustered by brand-name drug manufacturer.

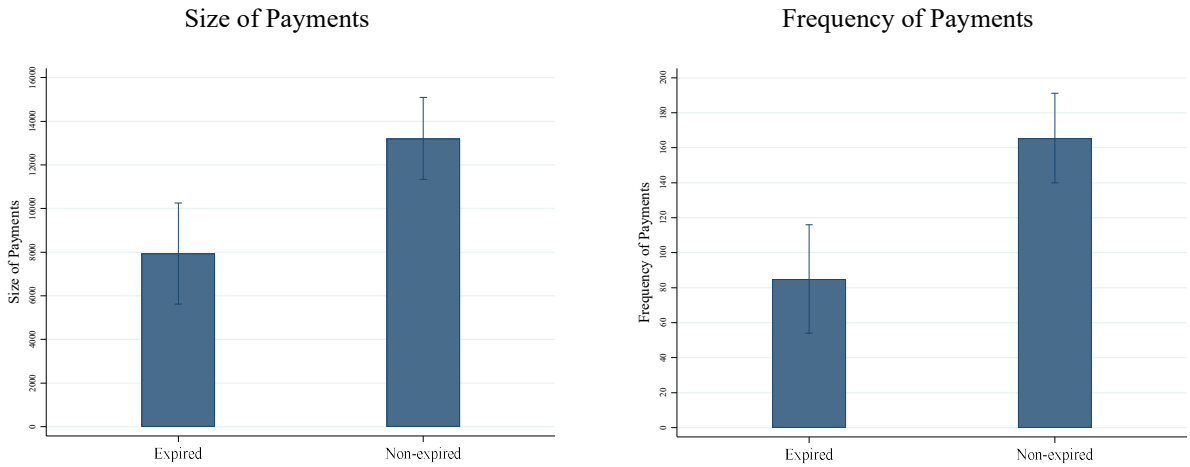
Table 1.3: Total payments, full sample (marginal effects)

	Total payments					Frequency of Payments	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lifecycle	-893.02*** (199.39)	-849.15*** (200.88)	-835.05*** (172.05)	-848.72*** (200.71)	-793.50*** (171.96)	-3.25 (2.53)	-2.98 (2.39)
Non-expired patent	5 489.04*** (1 241.97)	5 254.29*** (1 229.69)	3 182.71** (1 529.11)	5 227.59*** (1 228.56)	3 013.38** (1 506.74)	82.60*** (22.08)	50.76** (23.84)
No generic alternative	2 116.14 (2 981.09)	1 942.07 (2 953.18)		1 954.56 (2 954.21)		75.47*** (28.56)	
Number of generic alternatives[11]			-1 906.64*** (524.11)		-1 875.88*** (527.43)		-34.22*** (7.97)
New uses/dosages approved		7 849.16** (3 387.46)		7 838.06** (3 387.87)	7 605.53** (3 399.04)	79.40** (31.68)	76.22** (31.75)
State adopted disclosure policies prior to Sunshine Act				-7 635.73*** (1 896.03)	-7 627.49*** (1 896.85)	-143.46*** (16.23)	-143.15*** (16.28)
Observations	186 732	186 732	186 732	186 732	186 732	186 732	186 732

Notes: Robust standard errors clustered by pharmaceutical company in parentheses: $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$. All models have year fixed effects, therapeutic classification fixed effects.

[11] Number of generic alternatives variable has also a square term. However, when converting and calculating marginal effects, the number of generic alternatives (without square term) is reported, as described in Deb, Norton and Manning (2017).

Auruskeviciene, Butkeviciene and Salciuviene (2015) argue that after patent expiry (when generic competitors enter the market) investments in promoting brand-name drugs tends to remain high. Promotion is used not only to gain but also to sustain the market share by maximizing the protection from generic substitutes. Contrary to that argument, the analysis in table 1.3 suggests that generic entry and loss of patent depresses innovator's promotional expenditures. Particularly, pharmaceutical companies appear to promote their products when drugs are still in the period of patent protection. Given that the promotional expenditures are positive, having a non-expired patent is associated with a 3,013 dollar increase in promotional payments and 51 more interactions per drug per state (columns 5 and 7). Figure 1.4 also indicates that both size and frequency of payments are higher when the drug is protected by a patent(s). Namely, given that the frequency of payments is positive, drugs that have non-expired patents on average are more aggressively promoted through frequent interactions with prescribers and hospitals, than drugs that have expired patents, everything else constant.



Notes: Estimates are from equation 1.3 with all other variables fixed at their sample means.

Figure 1.4: Patent expiration and payments

When a generic is introduced into the market previously monopolized by the brand-name drug, the generic drug normally enters at a 20 percent discount from the branded medication within six months of launch, and the price falls quickly from that point. Eventually, most generics are priced at 80 to 85 percent discount from their name-brand equivalents (Feldman, 2018), significantly depressing brand-name producer's sales revenues. Therefore, to maximize the monopoly profit extraction before facing shrinking market share and revenues, the brand-name drug producers appear to increase promotional payments when no direct competition is available. Given, that the promotional expenditures and frequency of payments are positive, with each additional generic alternative in the market the promotions to prescribers and hospitals decline by 1,876 dollars, while interactions with prescribers decline by 34 visits per drug per state (columns 5 and 7).

Brand-name drug producers sometimes introduce new dosages or new uses of an existing drug to the market. Several qualitative case studies have suggested the efficacy of such strategies in extending patent protection and offsetting generic competition (Kakkar, 2015). Table 1.3 indicates that introducing new uses or dosages of a drug is associated with the increased size of payments by 7,605 dollars and increased interactions with prescribers and teaching hospitals by 76 per drug per state (columns 5 and 7). The table also shows that the brand-name drug producers decrease promotional payments by 793 dollars (per state) with every additional year in a drug's lifecycle (column 5), given that the promotional expenditures are positive. It is interesting to note, however, that introducing new uses or dosages leaves the size of promotional payments almost unchanged throughout a drug's lifecycle (figure 1.5).

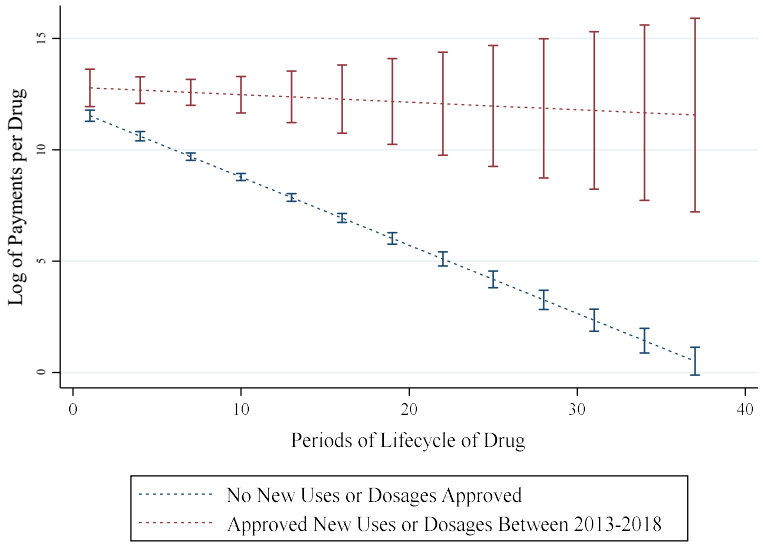
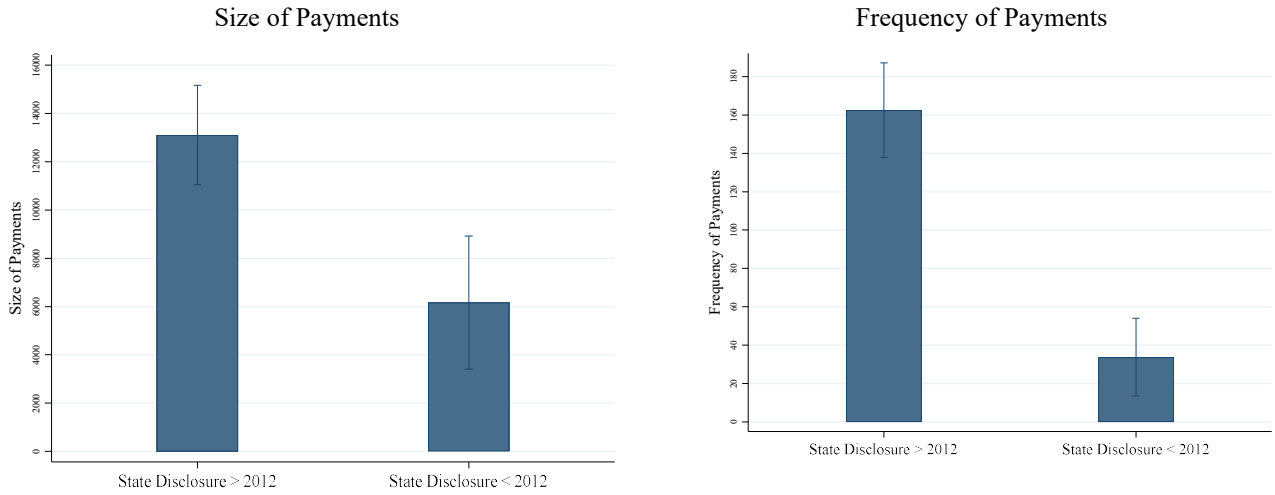


Figure 1.5: Payments by approval status of new uses or dosages of a drug

Finally, the states that did not adopt disclosure policies prior to the Sunshine Act on average receive 7,627 dollars more and have 143 more interactions per drug (columns 5 and 7), given that the size and frequency of payments are positive (also demonstrated in figure 1.6).



Notes: Estimates are from equation 1.3 with all other variables fixed at their sample means.

Figure 1.6: Payments by state disclosure policies

Next, I investigate the behavior of pharmaceutical promotions by examining different combinations. Although table 1.4 cannot be interpreted without further calculations, it shows the directions and significance of various combinations (interaction terms) on the decision of whether or not to spend on a drug's promotion (Logit model) and how much to spend (GLM model). Particularly, table 1.4 indicates that the likelihood of payment per drug increases when a drug is protected by a patent(s), has no generic competition or has a new uses or dosages approved in 2013-2018. The combination of those factors may indeed decrease the likelihood of promoting the drug to the hospitals and physicians. However, the results of second part of the model (GLM) indicate that such combinations have indistinguishable from zero effect on the size of promotional payments.

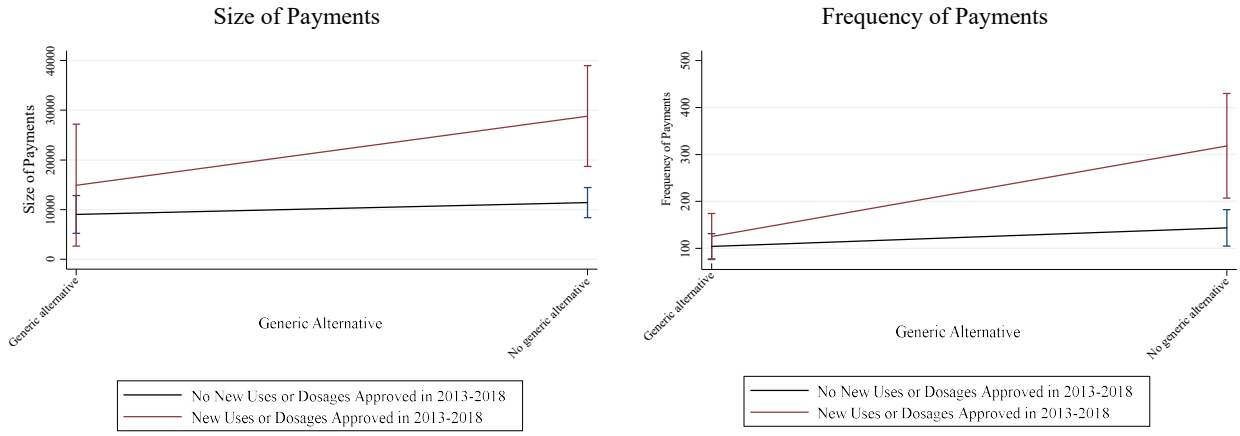
Investigating both size and frequency of payments reveals that not having a generic alternative and having new uses or dosages approved in the period of interest is associated with more frequent interactions and larger sized payments compared to the reference group. To extract monopoly profits, pharmaceutical companies invest more in promotional payments while drug is not facing generic competition. Thus, from revenue maximization perspective, it is more sensible to aggressively promote new uses or dosages of the drug (and attempt to shift the market) before the drug faces a generic competition (please refer to figure 1.7 below). After the entry of generic competition, decline in prices and revenues and most importantly, the shift in the market towards the generic alternative, aggressive promotion of the new uses or dosages of the drug would no longer be as profitable.

Table 1.4: Total payments, different combinations

	(1)	(2)	(3)	(4)
	Logit			
Lifecycle (years since FDA approval)	-0.06*** (0.02)	-0.06*** (0.02)	-0.05*** (0.02)	-0.07*** (0.02)
New uses or dosages approved in 2013-2018	1.47*** (0.27)	2.31*** (0.28)	1.99*** (0.27)	2.85*** (0.32)
Non-expired patent	1.01*** (0.15)	1.08*** (0.16)	0.67*** (0.15)	1.72*** (0.24)
No generic alternative	0.45*** (0.17)	0.41** (0.17)		1.32*** (0.31)
Number of generic alternatives			-0.34*** (0.04)	
Square number of generic alternatives			0.01*** (0.00)	
New uses or dosages & non-expired patent		-1.55*** (0.29)	-1.23*** (0.28)	-2.37*** (0.43)
New uses or dosages & no generic alternative	-0.68** (0.32)			-1.77*** (0.62)
Non-expired patent & no generic alternative				-1.39*** (0.35)
New uses or dosages & non-expired patent & no generic alternative				2.08*** (0.69)
State adopted disclosure policies prior to Sunshine Act	-0.42*** (0.02)	-0.42*** (0.02)	-0.42*** (0.02)	-0.42*** (0.02)
	GLM			
Lifecycle (years since FDA approval)	-1 318*** (392.2)	-1 323*** (393.1)	-1 291*** (335.4)	-1 357*** (404.4)
New uses or dosages approved in 2013-2018	4 680 (6 016)	2 239 (9 786)	1 522 (9 701)	11 935 (8 726)
Non-expired patent	3 519 (2 434)	2 840 (2 536)	1 162 (3 102)	7 273** (3 273)
No generic alternative	525.6 (6 025)	1 056 (6 039)		7 509 (5 013)
Number of generic alternatives			-1 531 (1 042)	
Square number of generic alternatives			44.41 (63.92)	
New uses or dosages & Non-expired patent		7 944 (11 196)	8 690 (11 095)	-10 871 (7 267)
New uses or dosages & No generic alternative	5 913 (8 540)			-35 946* (20 836)
Non-expired patent & No generic alternative				-9 028 (6 096)
New uses or dosages & Non-expired patent & No generic alternative				46 325* (24 156)

State adopted disclosure policies prior to Sunshine Act	-12 902*** (3 865)	-12 898*** (3 865)	-12 912*** (3 870)	-12 900*** (3 866)
Observations	186 732	186 732	186 732	186 732

Notes: Robust standard errors clustered by pharmaceutical company in parentheses: *** $p < 0.01$,** $p < 0.05$,* $p < 0.1$. All models have year fixed effects, therapeutic classification fixed effects.



Notes: Estimates are from interaction term between variables generic availability and new uses or dosages approved by FDA. All other variables described in equation 1.3 are fixed at their sample means.

Figure 1.7: New uses or dosages and no generic alternative

Table 1.4.1 below presents the calculations of marginal effects of table 1.4. The retransformation and calculation of an average marginal effect of an interaction term between two variables, as discussed in Deb, Norton and Manning (2017), results in values for separate variables. To obtain the marginal effects of interaction terms, further calculations were done. Table 1.4.1 calculates first the values for separate variables, then using pairwise comparison method calculates the marginal values of interaction terms.

Table 1.4.1: Marginal effects, total payments

	(1)	(2)	(3)	(4)
Lifecycle (years since FDA approval)	-848.28*** (200.34)	-847.84*** (200.76)	-792.79*** (172.06)	-884.31*** (204.99)
New uses or dosages approved in 2013-2018	8 671.69** (4 127.75)	8 563.45* (4 380.49)	8 006.56* (4 241.54)	8 528.84** (4 283.19)
Non-expired patent	5 248.60*** (1 225.49)	5 091.35*** (1 117.572)	2 993.27** (1 410.73)	3 774.16** (1 705.53)
No generic alternative	1 949.19 (2 792.25)	1 959.431 (2 954.031)		909.251 (3 162.14)
State adopted disclosure policies prior to Sunshine Act	-7 646.28*** (1 895.90)	-7 647.09*** (1 895.99)	-7 636.12*** (1 896.74)	-7 637.577*** (1 895.61)
Number of generic alternatives			-1 877.61*** (522.47)	
Pairwise calculations of interaction terms				
No generic alternative & New uses or dosages	1 430.46 (5 756.01)			
Non-expired patent & New uses or dosages		856.95 (8 016.42)	2 013.39 (7 673.35)	
Non-expired patent & New uses or[12] dosages & No generic alternative				12 338.75 (10 735.01)
Non-expired patent & New uses or[13] dosages & No generic alternative				-923.34 (5 331.51)
Observations	186 732	186 732	186 732	186 732

Notes: Robust standard errors clustered by pharmaceutical company in parentheses: *** $p < 0.01$,** $p < 0.05$,* $p < 0.1$. All models have year fixed effects, therapeutic classification fixed effects.

Results in table 1.4.1 show that the promotional payments tend to decline with each year of a drug being in the market. As a drug establishes in the market, promotional payments slowly fade away by 884 dollars per drug per state (column 4). Promotional payments increase when new uses and dosages of the drug are approved by FDA. According to estimates in table 1.4.1,

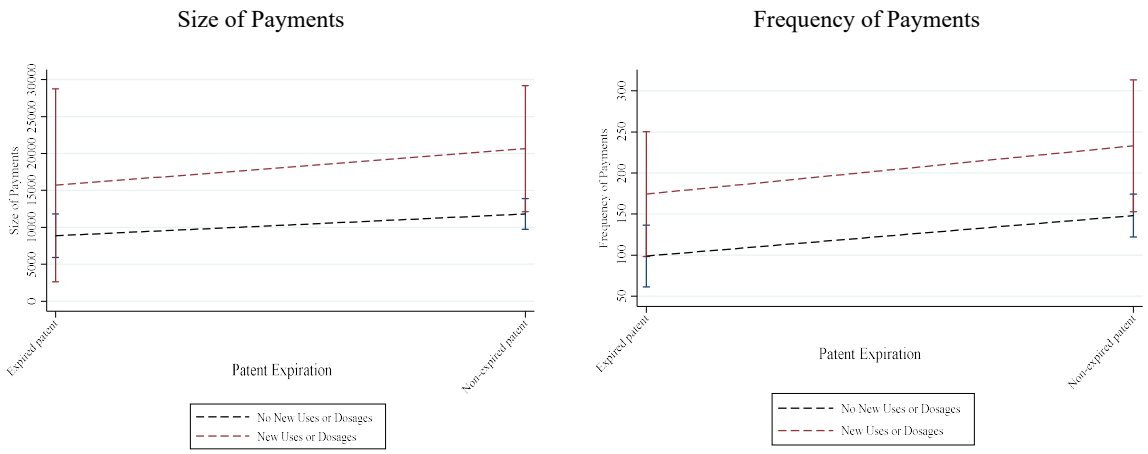
[12] Patent expiration is the comparison point in this triple interaction term.

[13] Generic competition (whether or not the drug has a generic competitor) is the comparison point for this triple interaction term.

pharmaceutical companies on average spend 8,529 dollars more per drug per state when the drug has a new use or dosage approved by FDA in the period of interest (such result also carries the secondary effect of having no generic competition and being protected by a patent(s)). Meanwhile, patent protection is associated with 3,774 dollars higher payments promotional payments per drug per state. Each additional generic competitor and adoption of disclosure policies prior to the Sunshine Act, as discussed before, are associated with lower payments.

Tables 1.4, 1.4.1 and 1.5, as well as figure 1.8 denote that the size and frequency of payments are not statistically different for drugs that have no new uses or dosages and non-expired patent compared to those that have new uses or dosages and non-expired patent(s). One explanation for such outcome is that pharmaceutical companies, in their efforts to shift the market before the entry of generic competitor, try to obtain approval for new uses or dosages while the drug is protected by patents. Meanwhile, obtaining new uses or dosages of the drug may allow the pharmaceutical company to apply for new patents or new exclusivities, thus starting the patent clock over and keeping generic competition away from the market.

As analyses have shown before, patent protection as well as not facing generic competition are associated with higher payments and more interactions with physicians and hospitals. However, the respective interaction terms of being in a period of patent protection and having no generic competition in tables 1.4.1 and 1.5 are not statistically significant. Such result may be driven by the fact that most drugs, while protected by patents, do not face generic competition. Only few drugs in the sample with “weak” patents were successfully challenged in the court and faced a generic competition before patent expiration date and/or had an authorized generic competition.



Notes: Estimates are from interaction term between variables non-expired patent and new uses or dosages approved by FDA. All other variables described in equation 1.3 are fixed at their sample means.

Figure 1.8: New uses or dosages and non-expired patent

Using the same techniques described in table 1.4.1, table 1.5 present the marginal effects calculations for dependent variable being frequency of payments. As table 1.5 indicates, having an FDA approved new use or dosage, being protected by patent(s) and having no generic competition are associated with more interactions with physicians. Each new generic competitor in the market is associated with 34 fewer interactions with physicians per drug per state, given that the interactions are positive (column 3). Meanwhile, states that adopted disclosure policies prior to the Sunshine Act observe 143 fewer interactions per drug compared to the states that did not adopt such policies.

Table 1.5 also suggests that none of the combinations is statistically significant. Some of those results are interesting and may add to information versus persuasion debate. As I'll thoroughly discuss next, if payments and visits to physicians have merely informative nature, one should observe increased interactions and payments when drug enters the market and when new uses or dosages of drug are FDA approved. Once the medical community is informed about

the drug and its uses, promotional payments should drastically decline. The results of interaction term for non-expired patent and FDA approved new uses or dosages reported in tables 1.4.1 and 1.5 are statistically indistinguishable from zero. This is more aligned with expectations of informative nature of payments, when payments would increase with FDA approved new uses or dosages of a drug, regardless of its patent protection period. Such results indicate that information may play a role in such interactions.

Table 1.5: Marginal effects, the frequency of the payments

	(1)	(2)	(3)	(4)
Lifecycle (years since FDA approval)	-3.25 (2.53)	-3.23 (2.53)	-2.96 (2.39)	-3.80 (2.47)
New uses or dosages approved in 2013-2018	87.04** (37.95)	91.60** (37.54)	79.47** (36.82)	90.93** (36.46)
Non-expired patent	82.59*** (21.94)	78.40*** (18.55)	49.22** (20.86)	54.55** (24.99)
No generic alternative	72.46*** (26.66)	75.46*** (28.57)		66.09** (28.75)
Number of generic alternatives			-34.18*** (7.98)	
State adopted disclosure policies prior to Sunshine Act	-143.56*** (16.24)	-143.56*** (16.23)	-143.24*** (16.28)	-143.44*** (16.26)
Pairwise calculations of interaction terms				
No generic alternative & New uses or dosages	20.44 (46.77)			
Non-expired patent & New uses or dosages		-15.58 (54.11)	9.49 (49.11)	
Non-expired patent & New uses or[14] dosages & No generic alternative				72.69 (63.50)
Non-expired patent & New uses or[15] dosages & No generic alternative				14.90 (42.98)
Observations	186 732	186 732	186 732	186 732

[14] Patent expiration is the comparison point in this triple interaction term.

[15] Generic competition (whether or not the drug has a generic competitor) is the comparison point for this triple interaction term.

Notes: Robust standard errors clustered by pharmaceutical company in parentheses: $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$. All models have year fixed effects, therapeutic classification fixed effects.

The pharmaceutical industry claims that drug promotions play a vital role in providing physicians with information regarding the differences between competing drugs available in the market (Handa, Vohra and Srivastava, 2013). Promotions result in raised awareness of their products and therefore have direct benefits for patients (Fischer et al., 2009). It has been also argued that drug promotions provide scientific and educational information to physicians concerning the risks and benefits of the product, thus ensuring patients are given the best treatment (Spurling et al., 2010). Others, however, disagree, showing that pharmaceutical companies aim to persuade prescribers to favor their drug. In a survey-based study, Caudill et al (1996) showed that the use of the information provided by pharmaceutical representatives was a positive predictor of prescribing costs. Meanwhile, DeJong et al. (2016) showed that promoting the drug of interest is associated with an increased rate of prescribing the promoted brand-name medication.

The hardship of estimating whether promotional payments have a persuasive effect, separate from their informational value, concerns the fact the information about the new drugs and their efficacy is often directly or indirectly obtained from pharmaceutical companies. In a study of ACE inhibitors with diuretics Ching and Ishihara (2012) attempt to isolate the impact of persuasive interactions by looking at a single chemical that is marketed by two drug firms under different brand names. Since the chemical is the same, the authors argue that a relationship between detailing[16] and brand-name drugs' market shares would be due to persuasion, not information. They find that overall, information plays a much larger role than persuasion in

[16] Face-to-face meetings where pharmaceutical sales representatives present information to physicians about drugs.

detailing. In another study, Engelberg, Parsons and Tefft (2014) separate information from persuasion by testing whether payments change the volume of prescription of branded drugs in the year a generic equivalent becomes available. They find that payments increase branded prescriptions. They conclude that payments have rather persuasive nature. The question of persuasion or information continues polarize medical community and remains to be answered.

I restrict the sample to non-expired patents, to examine if there are any changes in drug promotion throughout the patent protection period. If a pharmaceutical company promotes drugs to inform the medical community about available treatment, once information is successfully spread in the medical community, a drastic decline in the size and frequency of payments would be observed. On the contrary, if the reason for promotion is persuading physicians to prescribe the drug of interest, a more modest decline in either size or frequency of payments, as well as other behavior (explained below) should be observed.

Table 1.6: The restricted sample of non-expired patents

	Total payments (1)	Total payments (2)	Frequency of payments (3)	Frequency of payments (4)
Lifecycle (years since FDA approval)	-1 097.78*** (293.87)	-1 098.49*** (293.76)	-4.17 (3.94)	-4.19 (3.93)
New uses or dosages approved in 2013-2018	9 454.68* (5 554.55)	9 443.14* (5 556.29)	95.49* (51.85)	95.26* (51.91)
State adopted disclosure policies prior to Sunshine Act		-10 318.62*** (2 722.74)		-193.82*** (22.36)
Observations	126 738	126 738	126 738	126 738

Notes: Robust standard errors clustered by pharmaceutical company in parentheses: $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$. All models have year fixed effects, therapeutic classification fixed effects.

Table 1.6 indicates that while the size of payments declines with each additional year by 1,098 dollars per drug per state (thus speaking in favor of the provision of information argument), the frequency of payments on average does not change when the drug is protected by patents (speaking in favor of the persuasion argument). Perhaps throughout a drug's life, pharmaceutical companies simply shift from costly interactions (such as speaker fees, and travel and lodging) to cheaper interactions (such as food and beverages). Table 1.6 suggests, that even if the drug is protected by a patent(s), FDA approved new uses or dosages of drug is still associated with both an increase in size of payments (by 9,443 dollars) and frequency of interactions (by 95). Such outcomes may also favor the provision of information argument. However, while protected by patents, promotional payments on average are 10,318 dollars less and frequency of payments are 194 less (per drug) in the states that adopted disclosure policies prior to the Sunshine Act. If payments are purely informational, one should not observe such decline in the size and frequency of payments in the states that adopted disclosure policies prior to the Sunshine Act. While several results point to persuasive nature of payments, the results of information versus persuasion debate are somewhat inconclusive based on the results of table 1.6. It seems to be that promotions serve both purposes.

Results by Drug and Year

The results reported in previous tables were from disaggregated data by states. Next, I examine aggregated payments and interactions to discuss the sheer size of promotional payments per drug. The results in table 1.7 indicate that pharmaceutical companies spend on average 235,773 dollars more (column 1) and have 3,707 more interactions (column 3) when a drug is

still protected by a patent, given that the promotional payments and interactions are positive. Each year in the market is associated with a decline in promotional payments by 47,190 dollars (column 1) and 258 less interactions (column 3). New uses or dosages approved in the period of interest on average are associated with an increase in promotional payments by 576,741 dollars and 5,872 more interactions (columns 1 and 3), while each new generic competitor in the market is associated with a decline in promotional payments by 75,065 dollars and 1,292 less interactions per drug (columns 2 and 4).

Table 1.7: Aggregated by drugs, marginal effects

	Total payments (1)	Total payments (2)	Frequency of payments (3)	Frequency of payments (4)
Lifecycle (years since FDA approval)	-47 190.92*** (12 597.73)	-43 695.21*** (11 146.89)	-258.11** (130.20)	-222.86* (126.24)
Non-expired patent	235 772.9** (93 110.29)	126 501.5 (95 079.45)	3 707.46*** (1 203.16)	2 351.31* (1 327.83)
New uses or dosages approved in 2013-2018	576 740.9** (230 895.4)	618 706.2** (262 522.9)	5 872.62*** (2 262.79)	6 077.56** (2 552.58)
No generic alternative	62 109.2 (160 025.6)		3 525.39** (1 471.47)	
Number of generic alternatives		-75 064.9*** (26 254.74)		-1 291.55*** (306.12)
Observations	2 764	2 764	2 764	2 764

Notes: Robust standard errors clustered by pharmaceutical company in parentheses: *** $p < 0.01$,** $p < 0.05$,* $p < 0.1$. All models have year fixed effects, therapeutic classification fixed effects.

Although the general trend appears to be that patent expiration, facing no generic competition and having FDA approved new uses and dosages in the period of observation are associated with higher promotional payments and more frequent interactions, the tables discussed above do not reveal if this is true for all types of payments. Tables 1.8.1 and 1.8.2

below discuss the differences in using various types of payments depending on a drug's lifecycle, patent expiration, generic competition and when introducing new uses or dosages of the drug to the market.

Results by Nature of Payments

It could be expected that education, speaker, travel and lodging related payments are used earlier in drug's life to inform the medical community about a drug. Those payments have a potential to increase when new uses or dosages of the drug are introduced to the market. Once information is successfully spread in the medical community, a rapid decline in such payments should be observed. Meanwhile, gift and entertainment and food and beverage payments may erode slower and be used at any point of a drug's lifespan. Food and beverage payments could be widely used early in drugs life to spread the information (prescribers are more likely to listen to a pharmaceutical sales representative if he/she visits them with food) but also may be used to keep and strengthen the relationship and thus influence and persuade prescribers later in a drug's lifecycle.

Table 1.8.1: The nature of payments, per state, marginal effects

	Speaker Fees	Consulting	Educational	Food & Beverage	Travel & Lodging
Size of Payments					
Lifecycle (years since FDA approval)	-694.25*** (144.02)	-64.96** (28.04)	-4.22 (3.73)	-94.63*** (36.38)	87.22*** (16.09)
Non-expired patent	3 209.72*** (1 159.85)	1 410.94*** (399.39)	148.97*** (37.38)	1 197.39*** (299.72)	665.89*** (173.07)
No generic alternative	-1 059.76 (1 838.94)	291.01 (285.23)	-45.34 (38.77)	1 189.04*** (434.51)	9.48 (221.36)
New uses or dosages approved in 2013-2018	2 155.58 (1 678.26)	985.82** (432.93)	17.21 (33.39)	1 371.30** (561.98)	342.85** (158.88)
State adopted disclosure policies prior to Sunshine Act	-6 621.93*** (1 040.05)	1 796.61 (1 625.75)	-95.32*** (21.48)	-2 329.95*** (268.75)	-787.62*** (93.19)
Frequency of Payments					
Lifecycle (years since FDA approval)	-0.33*** (0.07)	-0.05*** (0.02)	-0.33*** (0.09)	-2.51 (2.49)	-0.35*** (0.07)
Non-expired patent	1.53*** (0.58)	0.56*** (0.19)	3.41*** (0.95)	76.78*** (22.51)	2.34*** (0.59)
No generic alternative	-0.18 (0.70)	0.53** (0.21)	0.14 (0.91)	65.93*** (25.17)	-0.07 (0.96)
New uses or dosages approved in 2013-2018	1.19 (0.82)	0.58* (0.31)	-0.42 (1.19)	59.21** (28.56)	1.28* (0.67)
State adopted disclosure policies prior to Sunshine Act	-3.26*** (0.46)	-0.36** (0.14)	-3.63*** (0.62)	-127.80*** (15.37)	-3.29*** (0.36)
Observations	176 148	181 170	172 314	186 192	179 442

Notes: Robust standard errors clustered by pharmaceutical company in parentheses: $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$. All models have year fixed effects.

Table 1.8.1 indicates that each additional year of the drug being in the market is associated with a decline in speaker fees by 694 dollars, consulting fees by 65 dollars, food and beverage by 95 dollars and travel and lodging by 87 dollars per drug per state. Meanwhile, with each additional year the frequency of speaker fee payments decline by 0.3, consulting by 0.05, provision of educational materials by 0.3 and travel and lodging by 0.4 per drug per state. The

rates of decline, as can be noted, vary. Having a non-expired patent is associated with increased speaker fees (by 3,210 dollars and 1.5 interactions), consulting fees (by 1,411 dollars and 0.6 interactions), food and beverage (by 1,197 dollars and 76.8 interactions) and travel and lodging (by 666 dollars and 2.3 interactions) related payments per drug per state. State disclosure policies seem to have a significant effect on speaker fees (decline by 6,622 dollars and 3.3 interactions), food and beverage (2,330 dollars and 128 visits) and travel and lodging related payments (788 dollars and 3.3 visits). Next, I aggregate payments and investigate the size and frequency of payments for the entire country.

Table 1.8.2: The nature of payments, aggregate, marginal effects

	Speaker Fees	Consulting	Educational	Food & Beverage	Travel & Lodging
Size of Payments					
Lifecycle (years since FDA approval)	-39 991.25*** (9 863.52)	-4 535.41*** (1 512.05)	-294.68 (219.65)	-5 080.7*** (1945.29)	-5 159.44*** (1244.49)
Non-expired patent	123 986.3** (57 793.9)	29 324.33** (13 155.68)	4 468.98** (1877.85)	63 639.75*** (15 710.27)	29 294.61*** (7 732.99)
No generic alternative	-41 556.45 (122 667.6)	7 137.63 (19 234.39)	-1659.83 (2241.91)	51 031.91** (22 730.17)	-1 739.49 (16 032.38)
New uses or dosages approved in 2013-2018	177 316 (127 506.3)	58 068.63*** (22 665.44)	950.59 (2428.32)	95 893.55** (39 177.91)	29 330.82** (13 659.93)
Frequency of Payments					
Lifecycle (years since FDA approval)	-19.23*** (4.56)	-2.81*** (1.07)	-19.75*** (5.04)	-144.65 (126.33)	-20.27*** (5.05)
Non-expired patent	56.06** (28.26)	3.77 (9.20)	64.64 (47.49)	4 110.46*** (1 189.05)	104.34*** (29.49)
No generic alternative	-5.68 (47.43)	19.55 (12.44)	-35.69 (72.96)	3 034.74** (1 285.11)	-13.76 (72.46)
New uses or dosages approved in 2013-2018	93.39 (63.17)	44.02* (25.72)	-11.77 (80.45)	4 222.78** (2 004.94)	107.95* (57.25)
Observations	3 160	3 184	3 127	3 018	3 141

Notes: Robust standard errors clustered by pharmaceutical company in parentheses: *** $p < 0.01$,** $p < 0.05$,* $p < 0.1$. All models have year fixed effects.

While speaker fees decline by 39,991 dollars with each additional year in the market, consulting payments decline only by 4,535 dollars, food and beverage by 5,081 dollars and travel and lodging by 5,159 dollars per drug. Being in the exclusive production period and protected by patents is associated with increased payments in food and beverage by 63,640 dollars, speaker fees by 123,986 dollars, consulting by 29,324 dollars and travel and lodging related payments by 29,295 dollars. Food and beverage payments are also higher by 51,032 dollars when a drug does not face generic competition. Meanwhile, having an FDA approved new use or dosage of a drug is associated with an increase in consulting related payments by 58,069 dollars, travel and lodging by 29,331 dollars and food and beverage related payments by 95,894 dollars.

The pharmaceutical industry claims that drug promotion plays a vital role in providing physicians with information regarding the differences between competing drugs available in the market (Handa, Vohra and Srivastava, 2013) and results in raised awareness of their products. However, it has been also argued that greater exposure to the drug promotion is related to higher prescription volume, low-quality prescribing behavior (Mintzes et al., 2013) and alteration of the prescribing habits of physicians (Akande and Aderibigbe, 2007). It appears that certain types of payments are more sensitive to the presence of generic competition and patent protection than others, pointing to the possibility of the persuasive nature of such payments. Food and beverage-related interactions increase by 4,110 and travel and lodging by 104 when a drug is still protected by patent(s). Having no generic competitor is associated with an increase in food and beverage related payments by 51,032 dollars and 3,035 interactions. Additionally, while all other types of payments decline in frequency with each additional year of drug being in the market, food and beverage-related payments do not (see tables 1.8.1 and 1.8.2). This speaks largely in favor of the persuasive nature of food and beverage payments.

1.5 Conclusion

Using various types of promotional expenditures for 712 brand-name drugs over 5 years (2014-2018), this chapter analyzed the patterns of competition surrounding patent expiration, generic entry in pharmaceutical markets and choice of promotional instruments. The results show that patent expiration and subsequent entry of generic competitors are strong predictors of promotional expenditures by pharmaceutical companies thus conveying their attempt to extract monopoly profits prior to facing direct competition from generic drug producers.

The paper posed the question of the strategies employed by pharmaceutical companies in their efforts to keep competition away from the market and enjoy longer periods of monopoly or duopoly power. The literature has provided examples of such cases, when a pharmaceutical company, in their efforts to shift the market from the existing versions of the drug (that are about to face patent expiration), introduced new dosages or found new uses of an existing drug, obtained new patents and shifted the market. Analyzing the behavior of pharmaceutical companies across 712 drugs, this chapter showed that the size and frequency of payments tend to increase after FDA approval of new dosages or new uses of an existing drug.

The study discussed the issues surrounding information and persuasion debate. The chapter showed that the size of payments decline with each additional year in the market, while the frequency of physician-pharmaceutical company interactions on average does not change when the drug is protected by patents. It argued that such behavior speaks in favor of the persuasion argument. The study also showed that when protected by patents, pharmaceutical companies pay less in size and frequency in the states that adopted disclosure policies prior to the Sunshine Act. This also was argued to speak in favor of persuasive payments. However, the

results of information versus persuasion are somewhat inconclusive, with size and frequency of payments increasing with FDA approved new uses or dosages of drug, a behavior that is associated with informational payment. Promotional payments seem to serve both purposes.

Finally, the chapter examined various types of payments and showed that promotional payments, such as speaker fees, consulting fees, travel and lodging and provision of educational materials tend to decline with each additional year of a drug being in the market. Food and beverage related payments (frequency of payments), however, seem to not decline with each year of being in the market, pointing on persuasive nature of such payments. Food and beverage payments, also, seem to be the most widely used tool by the pharmaceutical companies. Given the findings of this study, I recommend:

1) To carefully craft policies that would allow informative payments, limiting or eliminating the possibilities for persuasive payments. For instance, a policy may allow certain types of promotional payments only for the first 2-3 years of drug being in the market.
2) The study showed that patent expiration and generic entry especially affect the size and intensity of food and beverage payments. The first step towards controlling pharmaceutical industry-prescriber financial relationships perhaps should be limiting food and beverage related interactions.
3) To limit possibilities of extending monopoly power in the market. Pharmaceutical companies use many tools at their display to extend drug's exclusive production period. One such tool is Orphan drug exclusivity. The number of approved orphan drugs in the U.S. far exceeds such approvals in Europe and Japan combined. The U.S.

needs to revisit the Amendments in Hatch-Waxman Act, making it harder to obtain unjustified exclusivities.

CHAPTER 2: WHO TAKES IT ALL? FOREIGN-TRAINED DOCTORS AND PHARMACEUTICAL PROMOTIONS

2.1. Introduction

Culture and social norms pervade every aspect of life and influence the interactions and choices of individuals (Parsons and Shils, 1990). Culture is shared set of values, norms, and beliefs of a group of people (Chiu et al., 2010; Fischer, 2012; Kuper, 1999) that can be activated through situational cues (Fischer et al., 2014). Social norms, meanwhile, refer to the acceptability of a specific behavior (Köbis, Iragorri-Carter and Starke, 2018). They indicate whether a behavior is moral and is based on widely shared beliefs (Fehr and Fischbacher, 2004).

In the United States and many other countries around the world, pharmaceutical manufacturers and distributors engage in medical marketing to influence physician decision-making, which translates into excess spending on prescription drugs and medical devices (George Washington University, 2009). Pharmaceutical sales representatives approach hundreds of thousands of physicians annually in the U.S. alone and aggressively promote their products. This study investigates whether the culture and social norms of a foreign-trained physician's country of origin and a host country's rules and regulations influence the decision of a foreign-trained internal medicine doctor to accept a promotional payment in the U.S.

Understanding how culture and social norms influence decision-making is crucial to comprehending promotional payment acceptance practices. Culture and social norms are, however, challenging to measure. Instead, various studies have linked them to corruption (Bicchieri and Rovelli, 1995; Tong, 2014; Achim, 2016; Halkos and Tzeremes, 2011), and the

aggregate indices of corruption have been used as proxies for culture and social norms in cross-country studies (Treisman, 2000; Serra, 2006; Fisman and Miguel, 2007; Banerjee, 2016). In this chapter, culture and social norms are also proxied by corruption indices. The act of accepting promotional payments fits well within the standard definition of corruption, that is, "the abuse of entrusted power for private gain" (source: Transparency International).

It has been argued that corrupt transactions do not always require immediate return. There can be a gap between transfer and counter-transfer and therefore most corrupt practices cannot be characterized strictly as market transactions (Blundo, 2008; Davies et al. 2009; Morris and Polese, 2014). Gift-acceptance (or promotional payment acceptance) creates the sense of debt that must be repaid in the future (Bourdieu, 1997). When corrupt exchanges are separated in time, actors can easily blur the corrupt nature of transactions (Hipp and Lawler, 2010; Jancsics, 2014) or gift acceptance.

Meanwhile, Acemoglu, Johnson, and Robinson (2006) argue that individuals succumb to corrupt practices if they have discretion, weak accountability, and a substantial monopoly of power at their disposal (Pena López and Sánchez Santos, 2013). They assert that institutions are the mechanisms through which social choices are determined and implemented.

Distinguishing between the effects of culture (social norms) and institutions and understanding the causes of payment acceptance is of central importance in reducing or preventing such practices. Inspired by the development literature on corruption, social norms and institutions, this paper evaluates the role of both cultural norms and legal enforcement on financial relationships between the pharmaceutical industry and physicians trained abroad.

This chapter shows that in the absence of rules and regulations, physicians from different countries with different corruption norms adopt somewhat similar behavior. However, the

propensity to accept promotional payments decreases among physicians from less corrupt countries when a host country's regulatory environment restricts the acceptance of such payments. Particularly, physicians from less corrupt countries accept less in promotional payments when restrictive hospital policies regarding payment acceptance are in place. Physicians from less corrupt countries also adopt different behavior with regard to promotional payments in states that adopted disclosure policies prior to the Sunshine Act. The Sunshine Act, also known as section 6002 of the Affordable Care Act, was passed in 2010, requiring medical product manufacturers to disclose to the Centers for Medicare and Medicaid Services (CMS) any payments or other transfer of value made to physicians or teaching hospitals (source: Centers for Medicare and Medicaid Services). Physicians from less corrupt countries accept less in promotional payments if they practice in states that voluntarily adopted disclosure policies prior to the Sunshine Act. The findings in this chapter also suggest that home country's corruption norms and host country's regulatory environment are both important predictors of corrupt behavior among physicians trained abroad.

This work is also inspired by the literature on gender and corruption (Swamy et al., 2001; Breen et al., 2017; Alatas et al., 2009). It finds a strong relationship between a physician's gender and propensity to accept promotional payments, with female physicians accepting less in promotional payments than their male colleagues. Finally, the study shows that each year of practicing medicine in the U.S. is associated with an increase in promotional payment acceptance.

In the light of the growing shortage of U.S-trained physicians, especially among primary care doctors, studying the behavior of foreign-trained physicians is timely and important. To my knowledge, no study has examined the relationship between the pharmaceutical industry and

foreign-trained physicians practicing in the United States from a socio-cultural and institutional perspective. The findings offer insights into the behavior of foreign-trained physicians, their background, and the hidden factors that might increase the likelihood and the size of accepted promotional payments. The study contributes to a growing literature concerning corruption, cultural and institutional norms, gender equality and physician-pharmaceutical industry relationships.

The rest of the chapter is laid out as follows. Section 2.2 provides an overview of the literature. A summary of the data is presented in Section 2.3. Empirical methods and results are presented in Section 2.4 and the paper closes with a discussion and conclusion in Section 2.5.

2.2. Literature Review

The pharmaceutical industry exercises considerable influence on physician prescribing practices through promotional payments (Caudill et al., 1996; George Washington University, 2009). Numerous studies have shown that physician-industry relationships are associated with increased prescribing of brand-name drugs (Windmeijer et al., 2006; Huang et al., 2005; Yeh et al., 2016). Physicians who receive payments from pharmaceutical companies are two to three times as likely to prescribe brand-name drugs to Medicare patients (Jones and Ornstein, 2016) as compared with those who do not receive payments (DeJong et al., 2016).

A crucial issue for patients and society at large is that treatment choices are made rationally, with patients receiving the best and most cost-effective drugs available. These goals are unlikely to be met if the reasons for prescription are distorted and tip the balance away from

patients' interests towards those of the pharmaceutical industry. With the number of medical professionals approached by pharmaceutical representatives annually exceeding 900,000 in the U.S. alone (source: Open Payments Database), the questions of what should be done to protect patient interests and which physicians are more likely to accept promotional payments are pressing.

The pharmaceutical industry uses various methods to influence physicians. A study of 2,938 physicians in 7 specialties demonstrated that 83.8 percent of physicians had a relationship of some form with the pharmaceutical industry (Campbell et al., 2010). The most common (70.6 percent) involved food in the workplace or the receipt of drug samples (63.8 percent).

Foreign-trained physicians play an important role in providing healthcare due to the type of medicine they specialize in and the areas of the country in which they practice. While U.S.-trained physicians tend to choose more lucrative specializations, such as dermatology and orthopedics, a large portion of general and preventative health care needs are filled by physicians who received their training outside of the United States (American Immigration Council, 2018). More than half (53.4 percent) of all foreign-trained physicians work in locations where income per-capita is below 30,000 dollars, and 42.5 percent of all physicians are foreign-trained in locations where per-capita income is below 15,000 dollars (see table C-2, Appendix C).

In the light of rapidly increasing medical costs, the study of foreign-trained physicians is especially timely and important today. The relationship between foreign-trained physicians and pharmaceutical industry has the potential not only to increase overall medical costs, but also contribute to growing wealth inequality. The significance of the study of foreign physicians' revealed preferences in accepting pharmaceutical promotional payments also rests on the fact that current and future shortages for primary care physicians are likely to be partially filled by

foreign-trained physicians (Zhang et al., 2020). Since those physicians lived and received their training outside of the United States and were exposed to different cultural and social norms, they may have different perceptions of corruption and wrongdoing.

Empirical studies suggest that the willingness of actors to engage in corruption reflects the universalistic social norms and values that people internalized in the countries where they grew up (Jancsics, 2014; Barr and Serra 2010; Fisman and Miguel, 2007). Values and beliefs are transmitted from generation to generation through primary socialization they represent a slow-moving component of culture (Guiso, Sapienza and Zingales, 2006). A study by DeBacker, Heim and Tran (2015) showed that corporations with owners from more corrupt countries tend to evade more taxes in the U.S. than their counterparts from less corrupt countries. The effect was especially strong for small corporations. Fisman and Miguel (2007) evaluated the role of social norms in corruption by studying parking violations among international diplomats living in New York City. They found strong persistence in corruption norms: diplomats from high corruption countries had significantly more parking violations.

If individuals do not internalize the anti-corruption norms in the host country, those who grew up in societies in which corruption is prevalent are more likely to act corruptly than individuals who grew up in societies where corruption is rare. But things look different when individuals internalize anticorruption norms. Barr and Serra's (2010) bribery experiment of Oxford University students showed that corruption levels in the student's country of origin was a good predictor of bribe acceptance among undergraduates. However, the same did not hold among graduate students. The study found that time spent in the host country (UK) was associated with a decline in the propensity to bribe, implying gradual subsidence in the influence of corruption norms from the country of origin.

Cameron et al. (2009) studied culture and corruption by engaging a large sample of students in Australia, India, Indonesia, and Singapore in a bribery game. The results were inconclusive. Although several cross-cultural variations in corrupt and anti-corrupt behavior were identified, the variations did not correlate with the level of corruption in each country. For instance, Cameron et al. (2009) found that an individuals' propensity to bribe were not significantly different in Australia, Singapore and Indonesia, and an individuals' propensity to accept a bribe were lower in Indonesia than in the less corrupt country of Singapore.

The literature on the determinants of corruption has argued that rules and regulations are important factors affecting corruption (Stigler, 1971; Laffont and Tirole, 1991; Djankov et al., 2002). Lederman, Loayza and Soares (2005) stress the role of institutions in determining the prevalence of corruption, while Halter, Coutindo de Arruda and Halter (2009) emphasize that a change of ethical standards and regulations in some organizations can reduce corruption. Fisman and Miguel (2007) also found that differences in parking violations by diplomats from high and low corruption countries converged following a change in law enforcement, implying that rules and regulations can overpower corruption norms.

Finally, it has been argued that women are more inclined to demonstrate altruistic and moral behavior (Eagly and Crowley, 1986; Eckel and Grossman, 1998; Glover et al., 1997) and are more public-spirited than men (Goertzel, 1983; Ones and Viswesvaran, 1998). Women tend to hold to higher standards of ethical behavior and are more concerned with the common good (Dollar, Fisman and Gatti, 2001). Thus, it has been asserted that increasing women's presence in public life can reduce levels of corruption (Swamy et. al., 2001). By contrast, Sung (2003) notes that observed associations between gender and corruption are misleading, spurious and mainly caused by a political system that promotes both gender equality and better governance.

This study investigates the characteristics of foreign-trained physicians and discusses the factors that influence the decisions of accepting promotional payments in the U.S. The work is part of a growing body of research on the importance of cultural background and institutions in explaining economic behavior.

2.3. Data

There are more than 247,000 physicians with medical degrees from foreign countries practicing in the United States, making up more than one-quarter of all physicians. Slightly more than half of foreign-trained physicians (or 128,099) practice in primary-care fields such as family medicine, internal medicine, and pediatrics. They constitute for 31.8 percent of all physicians in those three specialties (American Immigration Council, 2018).

This chapter focuses on foreign-trained internal medicine doctors and their behavior with regard to accepting promotional payments. The choice of internal medicine doctors is driven by the fact that hospitals employ more primary care physicians than other subspecialties, which allows me to capture more variation in physician background in each hospital.

I use Open Payments 2014-2018 data to track individual promotional payments. The dataset contains over 11 million observations (or unique entries) providing detailed information on the date and size of a payment to each foreign-trained physician from pharmaceutical providers, the nature of the payment (e.g., food, speaker fees, travel etc.) and number of interactions between a physician and pharmaceutical sales representatives. Payments related to royalties, ownership, dividends, and charities are excluded from the sample because of their non-marketing nature. Since Open Payments do not record samples of drugs provided to physicians by pharmaceutical sales representatives, drug samples are also not included in the study.

The Open Payments database includes only the dates and positive values of payments to physicians. When no payment is accepted by a physician in a certain year, a zero payment does not appear in the database. If the paper used the database as is, without making corrections for the absence of zero payments, then the study would run the risk of overestimating the effects of cultural (corruption) norms, gender and institutions on payment acceptance. Therefore, zero payments were added to the data for cases when foreign-trained physicians did not accept payments from pharmaceutical companies.

Although the study largely investigates overall payments from the pharmaceutical industry, in some analyses various types of payments from the pharmaceutical industry were combined into obligatory and non-obligatory types of payments. The obligatory or quid pro quo payments are awarded by pharmaceutical companies in exchange for services. They include speaker, consulting and travel and lodging-related payments. Non-obligatory payments do not assume any contractual obligation and heavily rely on a physician's good will of prescribing the medicine and acting in favor of pharmaceutical company. Such payments include food and beverage, provision of educational materials and gift related payments.

The CMS National Provider Identifier File (NPIF) was used to identify foreign-trained physicians. CMS NPIF provides information about physician characteristics including provider name, provider business location and mailing address, specialty code(s), provider's sex, medical school attended and year of graduation. Unfortunately, CMS NPIF only provides information about medical schools that the U.S.-trained physicians attended. Medical schools that foreign-trained physicians attended are identified as "Other" and no further information is provided about names of medical schools or the countries in which they are located. After identifying foreign-trained internal medicine doctors through CMS NPIF, information on attended medical

schools and countries was hand collected. The sample consists of 2,905 foreign-trained internal medicine doctors who are employed in U.S. teaching hospitals.

To examine the effect of country of origin's cultural (thus corruption) norms on the propensity of a foreign-trained physician to accept promotional payments in the host country, the study utilizes various corruption indices, including *control of corruption*, *bribery incidence* and *bribery depth*. The *control of corruption index*, taken from Worldwide Governance Indicators[17], reflects perceptions of the extent to which public power is exercised for private gain (source: World Bank). The larger the index measure, the stronger is the enforcement of rules and governance. Estimates for this index range from approximately -2.5 (weak) to 2.5 (strong). The corruption measures are available starting from 1996. Since physicians immigrated to the United States in different years, an average for the period 1996 to 2010[18] was taken for each country in the database.

Other measures used in this study are bribery incidence and bribery depth. Bribery depth is the percentage of instances in which a firm is either expected or requested to provide a gift or informal payment during solicitations for public services, licenses or permits (source: World Bank). Bribery incidence, meanwhile, is the percent of firms experiencing at least one bribe payment request across 6 public transactions dealing with utilities access, permits, licenses, and taxes (source: World Bank).

[17] The Worldwide Governance Indicators (WGI) summarizes the views of enterprises, citizens and survey respondents on the quality of governance in industrial and developing countries. These data are gathered from several surveys of institutes, think tanks, non-governmental organizations, international organizations, and private sector firms.

[18] The Open Payment database used in this paper covers years 2014 to 2018. Since a physician needs to pass medical board exams and 3 years of residency program to work as an internal medicine doctor in the U.S, 2010 was chosen as an upper bound for immigration year. The status of every physician was checked in the database to confirm that they were licensed practicing internal medicine doctors in the U.S during the period of observation.

Eliminating corruption is a major concern for many countries. Dollar, Fisman and Gatti (2001) use country-level data for a sample of more than 100 countries and find that the greater the representation of women in the country's legislative body, the lower the country's level of perceived corruption. Swamy et al. (2001), using both micro-level survey data from a range of countries and country-level data, find that, on average, women are less tolerant of corruption than men. Meanwhile, Breen et al. (2017) find that women in positions of influence are associated with less corruption. However, Alatas et al. (2009) argue that gender differences in corruption behavior may not be universal. The data used in this study indicates that female physicians on average accept lower and fewer payments than their male colleagues (see table 2.1).

The statistical models used in this chapter also account for the state in which a foreign-trained physician practices medicine. A number of states either banned gifts to physicians or required disclosure of gifts from pharmaceutical companies prior to adoption of the Sunshine Act. The study exploits such geographic variation to analyze the relationship between gift regulations, disclosure policies, and acceptance of promotional payments by foreign-trained physicians. This variation allows one to assess the relative strength of corruption norms in the country of origin against institutional factors in the host state in determining promotional payment acceptance among foreign-trained physicians.

The sample used in this study is limited to foreign-trained internal medicine doctors who work at U.S. teaching hospitals or hospitals that are affiliated with medical universities. The choice of hospital type was driven by the availability of detailed information on Conflict of Interest (COI) policies that regulate pharmaceutical industry-physician relations. The COI data was hand collected from Institute of Medicine as a Profession and respective hospitals' COI

handbooks. I label COI policies as 1) no or permissive policies (when hospital policy does not address or restrict how much a physician can accept in a certain type of payment), 2) moderate policies (when there is an upper limit[19] set by a hospital with regard to acceptance of certain types of payments), 3) stringent policies (when a physician is not allowed to accept any payment from the pharmaceutical industry).

Using COI data, a hospital policy index was constructed by combining gift, speaker, consulting, meal, travel and lodging and vendor relation policies by calculating respective z scores for each domain. In some analyses, I utilize a high versus low restrictive hospital policy index by a *division at the median method*. The high category of the hospital policy index mostly contains hospitals with stringent policies. The low category of the hospital policy index mostly contains hospitals with permissive and some moderate policies. It should be noted, however, that the study is limited to official hospital policies and cannot claim anything about the implementation of COI policies and acceptance norms within departments.

This study controls for the size of the hospital where a foreign-trained physician works. Hospital size, among others, is often measured by the number of licensed beds (source: American Hospital Association). For the purpose of this study, the number of beds was hand-collected from sources such as American Hospital Association and hospital websites. Hospitals were then divided into small (less than 50 beds), medium (50-500 beds) and large (more than 500 beds) size categories.

The timing of receiving the license to practice medicine in the U.S. was also hand collected. This permits examination of how individual behavior may evolve over time in the host country. Finally, the study accounts for factors such as the difference between the U.S. and the

[19] The upper limit may vary depending on the type of payment. For instance, for food and beverage payments, the limit may be set at 50 dollars, while for speaker and consulting fees it may reach as high as 5,000-10,000 dollars.

country of origin's Gross Domestic Product per capita (based on purchasing power parity, PPP), geographic region where the country of origin is located, and year of payment.

Table 2.1 presents descriptive statistics for size and frequency of payments (for more detailed information about payments by countries please refer to table D-1 in Appendix D).

Table 2.1: Descriptive statistics

	Size of Payments		Frequency of interactions (payments)		
	Mean	Standard Deviation	Mean	Standard Deviation	N
Payments	469.28	3 753.95	17.35	40.15	14 237
Payments to male physician	547.79	1 636.65	22.71	47.33	7 461
Payments to female physician	382.84	5 162.12	11.46	29.25	6 776
Payments by years of practicing medicine in the U.S.					
Payments in early career (<5 years)	132.48	689.08	4.75	17.78	2 655
Payments in mid-career (5-10 years)	220.15	1 099.04	8.36	24.18	4 212
Payments in late-career (10+ years)	732.99	5 120.26	27.03	49.69	7 370
Payments by hospital size					
Small-sized hospital (< 50 beds)	69.47	100.56	3.3	7.49	20
Medium-sized hospital (50-500 beds)	388.89	1 227.18	17.41	38.91	5 452
Large hospital (>500 beds)	520.49	4 686.10	17.36	40.96	8 760
Payments by State Policies					
Payments if state adopted disclosure policies prior to the Sunshine Act	95.21	468.95	3.95	18.85	1 256
Payments if state did not adopt disclosure policies prior to the Sunshine Act	505.47	3 926.78	18.65	41.41	12 981
Payments by hospital policies					
Highly restrictive hospital policies	478.89	5 734.09	12.57	35.06	5 611
Less restrictive hospital policies	466.62	1 398.38	20.24	42.63	7 862

Payments by region					
East Asia and Pacific	485.29	1 363.89	20.10	44.05	1 240
Europe and Central Asia	632.84	1 595.46	25.48	48.24	2 440
Latin America and the Caribbean	552.96	1 760.26	21.51	45.03	3 017
Middle East and North Africa	350.24	798.54	17.99	43.07	1 264
North America	355.48	913.85	14.57	32.78	105
South Asia	415.74	5 823.54	11.74	31.36	5 349
Sub-Saharan Africa	198.46	617.86	9.73	27.13	822

2.4. Empirical Strategy and Results

The primary empirical strategy explores the differences in accepting promotional payments by country of origin's corruption index, host country's rules and regulations, a physician's gender and other characteristics. One of the challenges associated with estimating such relationships is that a large percentage of physicians did not accept any promotional payment, thus there is a large mass point at zero and positive values (see figure 2.1).

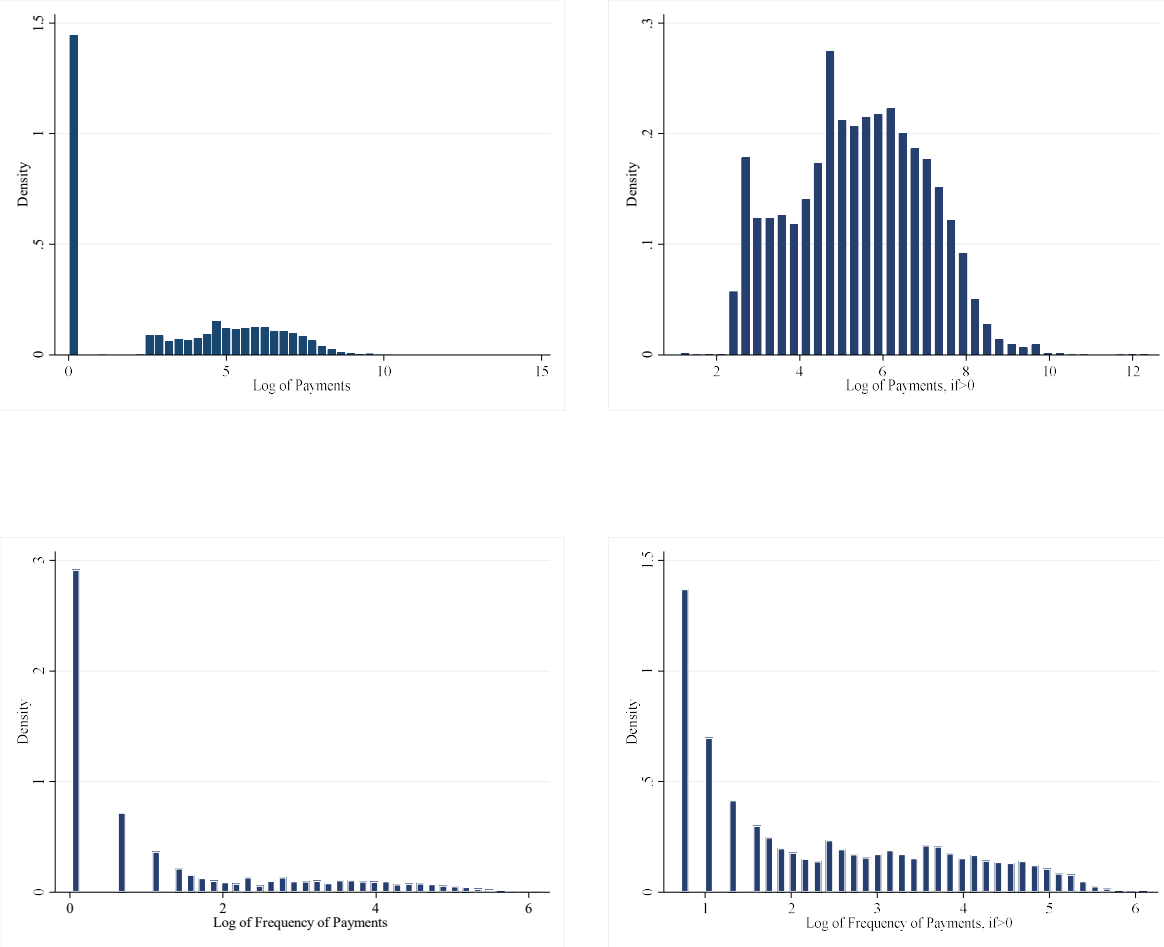


Figure 2.1: The size and frequency of payments

Using two separate models for the likelihood of payment acceptance and how much to accept given a decision to accept a payment seems to be the best fit for the data[20]. The probability of observing a positive-versus-zero payment is estimated using the Logit model. Then, conditional on a positive payment, an appropriate regression model is chosen. The choice of second model depends on the characteristics of the dependent variable. This paper utilizes the

[20] As explained in chapter 1, Tobit model is not a good fit for such data. The Heckman selection model (Heckman,1979) is not a good fit in this context either, since zeros are not missing values, but rather a physician's choice to not accept payments. Figure 2.1 also shows a gap between mass point at zero and positive values, making the Heckman selection model less appropriate (Greene, 2012).

GLM model. The GLM generalizes the ordinary linear regression model by allowing the expectation of the outcome variable to be a function (known as the link function) of the linear index of covariates, not simply the linear function of the index. It also explicitly models heteroscedasticity (Belotti et al., 2015).

Specification Tests for GLM

The Box-Cox (Box and Cox, 1964) and Park tests (Park, 1966) are used to determine the appropriate functional form and the distribution family for modelling the continuous part of the dependent variable. When conducting Box-Cox test, the estimated coefficient was close to zero (δ = 0.0002), prompting the choice of natural log transformation (explained in chapter 1). Meanwhile, the modified Park test (Park, 1966) determined the choice of gamma link.

Figure 2.1 indicates that frequency of interactions (payment)s can be also treated as a continuous variable. Tests to determine power and link functions for the dependent variable of frequency of interactions were conducted in the same fashion. The GLM model with log link and the gamma distribution was found to be the best fit.

Model specification

The dependent variable in the main econometric specification is total payments per physician. The paper utilizes two different models to calculate the probability and the size of accepted payments. The first model examines the likelihood of accepting payment. Independent variables include physician j's gender, the length of practicing medicine, the corruption norms of

a physician j's country of origin i, rules and regulations in the host country (the United States), as well as physician- and country-of-origin-related other characteristics.

$$\Pr(TotalPayments_{ijm} > 0) = \nu_0 + \nu_1 PhysicianGender_j + \nu_2 YearsInPractice_j + \nu_3 Corruption_{ij} + \nu_4 HospitalPolicies_j + \nu_5 StatePolicies_{mj} + \nu_6 Controls_{ijm} \quad (2.1)$$

where, $PhysicianGender_j$ is a dummy variable that assigns a value of 1 to a female physician j. $YearsInPractice_j$ is the length (in years) of practicing medicine in the U.S by a physician j. $Corruption_{ij}$ is physician j's country of origin i's control of corruption index. $HospitalPolicies_j$ is an index developed based on hospital's Conflict of Interest policies where physician j works at. $StatePolicies_{mj}$ variable indicates if physician j practices medicine in the state m that adopted disclosure policies prior to the Sunshine Act. $Controls_{ijm}$ include physician j's country of origin characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, the size of the hospital, as well as year fixed effects.

The study also investigates the combined effects (interaction terms) of country of origin's corruption index and hospital policies, control of corruption index and gender, as well as country of origin's corruption index and state policies. Since the paper follows individual physicians practicing medicine in the U.S., it is important to examine the related question whether there is any evolution of behavior in the host country. Barr and Serra's (2010) bribery experiment showed that time spent in the host country is associated with a decline in propensity to bribe. This chapter studies the interaction term of country of origin's corruption index and years of practicing medicine in the U.S. to track the change in behavior in the host country.

The second model examines the size of the payments (for physicians who accept payments) using the independent variables identified above. The equation of interest in a simplified form is the following:

$$\mathrm{E}(\mathrm{Log}(TotalPayments_{ijm}) \mid TotalPayments_{ijm} > 0) = g^{-1}(\beta_0 + \beta_1 PhysicianGender_j + \beta_2 YearsInPractice_j + \beta_3 Corruption_{ij} + \beta_4 HospitalPolicies_j + \beta_5 StatePolicies_{mj} + \beta_6 Controls_{ijm}) \quad (2.2)$$

where g^{-1} is the link function in the GLM model. It is important to note that those two models do not make any assumption about the correlation between the errors of equations (2.1) and (2.2). They do not need to be independent to get consistent estimates of the parameters ν and β.

Results

In the analyses presented below both size of payments (total payments) and frequency of interactions (frequency of payments) were used as dependent variables. Logistic model results are reported in odds ratios and show the likelihood of accepting any payment or having any interaction with pharmaceutical sales representatives in the period of observation. The fixed effects include year effects, hospital size, the distance between U.S. and country of origin's GDP per capita PPP and region (the location of the country of origin).

Table 2.2: Size and frequency of payments

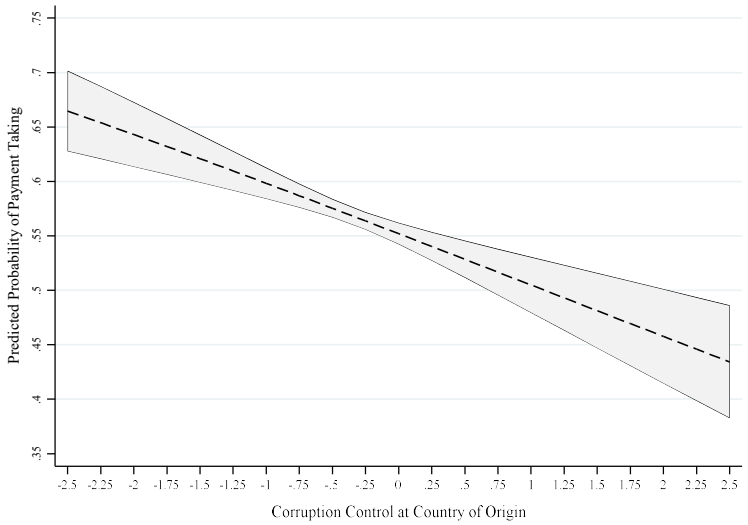
	Total Payments		Frequency of Interactions	
	Logit (Odds Ratio)	GLM	Logit (Odds Ratio)	GLM
	Payment > 0 (1)	Log Payment > 0 (2)	Interaction > 0 (3)	Log Interaction > 0 (4)
Control of Corruption	0.804*** (0.035)	-0.006 (0.088)	0.804*** (0.035)	0.088** (0.041)
Hospital Policy Index	0.752*** (0.015)	0.115*** (0.037)	0.752*** (0.015)	-0.040** (0.020)
Gender (female=1)	0.669*** (0.026)	-0.246*** (0.062)	0.669*** (0.026)	-0.319*** (0.038)
Years of practicing medicine in the U.S.	1.060*** (0.003)	0.067*** (0.005)	1.060*** (0.003)	0.054*** (0.003)
State adopted disclosure policies prior to the Sunshine Act	0.321*** (0.024)	-0.832*** (0.111)	0.321*** (0.024)	-0.650*** (0.114)
Observations	12 984	7 358	12 984	7 358

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

The results in table 2.2 indicate that higher measures of country of origin's control of corruption are associated with lower likelihood of accepting promotional payments and interacting with pharmaceutical sales representatives. Particularly, as the country of origin's control of corruption index increases by 1 unit, the likelihood of accepting payments decreases by 20 percent. This implies that as a country of origin becomes less corrupt (increase in control of corruption index), a foreign-trained physician becomes less likely to accept promotional payments. Results are summarized graphically in figure 2.2, illustrating how the predicted probability of payment acceptance decreases with control of corruption practices in foreign-

trained physician's country of origin. These results are aligned with Fisman and Miguel (2007) findings on the persistence in corruption norms.

While corruption norms are associated with higher likelihood of payment acceptance and are statistically significant at 1 percent level, the corruption norms seem to have no statistically significant effect on the size of accepted payments (GLM model, column 2), conditional on accepting any payment.



Notes: Estimates are from equation 2.1 with all other variables fixed at their sample means.

Figure 2.2: Control of corruption index

The results in table 2.2 also indicate that the likelihood of accepting payments and the likelihood of interaction with pharmaceutical representatives are lower among female physicians compared to their male counterparts. The same applies to the size of payments and the frequency of interactions. Given that the payments are positive, female physicians on average accept 24.6 fewer log dollars (column 2) and interact with pharmaceutical sales representatives 31.9 percent

less (column 4) than to their male colleagues. One likely explanation from the academic literature is that female physicians adopt higher moral standards with regards to interaction and acceptance of payments from pharmaceutical industry (Swamy et al., 2001). Another likely explanation could be that female physicians are approached less (Alssageer and Kowalski, 2012) and offered less by pharmaceutical representatives than their male counterparts. Unfortunately, the data used for analyses does not allow to tease out the reasons for lower frequency of interaction and smaller size of accepted payments by female physicians. Table 2.2 shows that the likelihood of accepting payments and the likelihood of interacting with pharmaceutical representatives increase with each year of practicing medicine in the U.S. The same applies to the size of payments and the frequency of interactions (payments). The results are consistent with Alssageer and Kowalski (2012) findings that physicians practicing for more than 10 years are more than three times as likely to meet a pharmaceutical sales representative at least once a week compared to the physicians who have 1–3 years of practice. Perhaps physicians develop stronger relationships with the pharmaceutical industry throughout years.

Table 2.2 reveals that physicians who practice in the states that adopted disclosure policies prior to the Sunshine Act are less likely to accept payments or interact with pharmaceutical representatives compared to their colleagues who practice in the states that did not adopt such policies. Physicians, practicing in states that adopted disclosure policies prior to the Sunshine Act, also tend to accept 83 percent less and interact 65 percent less with pharmaceutical representatives.

A study by King and Bearman (2017) compared hospital gift acceptance policies and showed that policies banning or limiting gifts from pharmaceutical representatives to physicians are

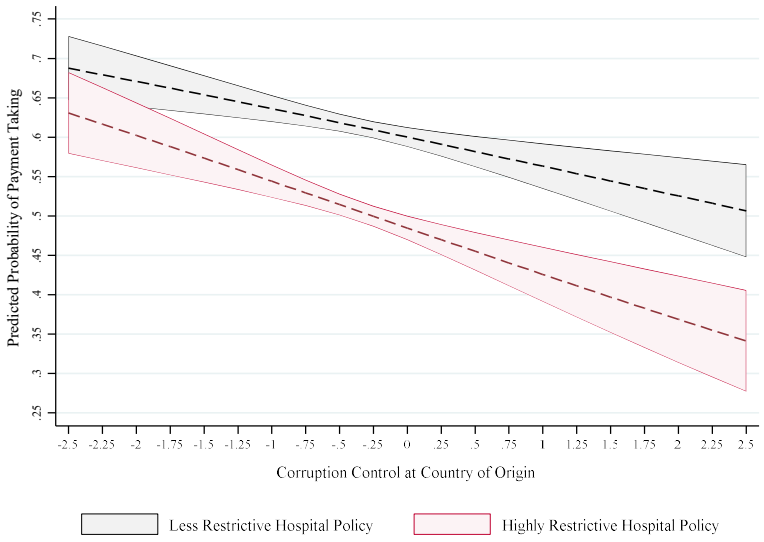
likely to be more effective than disclosure policies alone. As table 2.2 indicates, more restrictive hospital policies are associated with decline in likelihood and size of accepted payments.

Next, I investigate the impact of hospital policies and corruption norms in greater depth by allowing the impact of each to vary according to the level of the other (I interact them). In the set of regressions presented in table 2.3, a division of hospital policy index into highly restrictive and less restrictive hospital policies was conducted. The results in table 2.3 are represented in figure 2.3. As can be seen in figure 2.3, highly restrictive hospital policies are associated with lower likelihood of payment acceptance and interactions with pharmaceutical sales representatives. It is interesting to note that highly restrictive hospital policies particularly affect the behavior (likelihood of payment acceptance) of physicians from less corrupt countries. One likely explanation is that in less corrupt countries citizens grow up following laws and regulations and are largely law abiding. Therefore, once they are exposed to highly restrictive hospital rules, they follow those rules more eagerly and change their behavior accordingly. On the contrary, restrictive hospital policies seem to be less effective among physicians from more corrupt countries.

Table 2.3: Hospital policies and control of corruption

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment >0 (2)	Interaction >0 (3)	Log Interaction >0 (4)
Control of Corruption	0.843*** (0.040)	-0.026 (0.093)	0.843*** (0.040)	0.092** (0.045)
Hospital Policy (highly restrictive)	0.590*** (0.026)	0.236*** (0.087)	0.590*** (0.026)	-0.117** (0.048)
Hospital Policy Index × Control of Corruption	0.907* (0.050)	0.046 (0.083)	0.907* (0.050)	-0.004 (0.059)
Observations	12 984	7 358	12 984	7 358

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$



Notes: Estimates are from interaction term between variables hospital policies and country of origin's control of corruption index, with all other variables described in equation 2.1 fixed at their sample means. Highly restrictive hospital policy index mostly contains hospitals with stringent policies. Less restrictive hospital policy index, meanwhile, contains those with permissive and some moderate policies.

Figure 2.3: Hospital policies and control of corruption

Next, I investigate the combined effect of state disclosure policies adopted prior to the Sunshine Act and corruption norms.

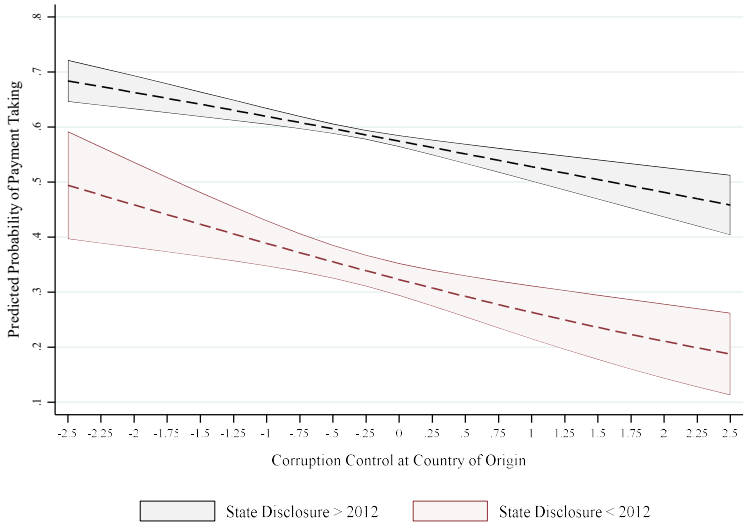
Table 2.4: State disclosure policies and control of corruption

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment >0 (2)	Interaction >0 (3)	Log Interaction >0 (4)
Control of Corruption	0.811*** (0.036)	-0.001 (0.089)	0.811*** (0.036)	0.116*** (0.041)
State Disclosure Policies	0.311*** (0.025)	-0.873*** (0.121)	0.311*** (0.025)	-0.881*** (0.093)
State Disclosure Policies × Control of Corruption	0.893 (0.082)	-0.103 (0.151)	0.893 (0.082)	-0.524*** (0.110)
Observations	12 984	7 358	12 984	7 358

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table 2.4 and figure 2.4 highlight an important phenomenon. Physicians from less corrupt countries change their payment acceptance and interaction behavior more drastically when laws and regulations are in place (i.e., state disclosure policies). This finding is opposite of Fisman and Miguel (2007) who found that diplomats from highly corrupt countries change their behavior drastically once laws and regulations were in place. Table 2.4 indicates that while norms and culture matter, just as Fisman and Miguel (2007) claim, policies in the host country matter too. The results are somewhat of a mix of Lederman, Loayza and Soares (2005), Halter, Coutindo and Halter (2009) and DeBacker, Heim and Tran (2015). They indicate that although

initially all physicians show high likelihood of promotional payment acceptance, once regulations are in place, cultural background affects their behavior of payment acceptance.



Notes: Estimates are from interaction term between variables state disclosure policies and country of origin's control of corruption index, with all other variables described in equation 2.1 fixed at their sample means.

Figure 2.4: State disclosure policies and control of corruption

Payment acceptance behavior may depend on the type of payment, whether the payment type is obligatory or non-obligatory in nature**.** The results reported in table 2.5 provide with a very interesting insight into acceptance of payments. They indicate that physicians from less corrupt countries are less likely to accept non-obligatory payments (such as food and beverage, educational and gift-related payments), but are more likely to accept obligatory payments (such as speaker fees, consulting and travel and lodging-related payments) compared to their counterparts from more corrupt countries. Unfortunately, the data do not allow one to investigate further whether such outcomes are due to physicians' tastes for certain types of payments or

pharmaceutical companies' preferences for physicians from a certain background (especially for speaking and consulting purposes).

Table 2.5: Obligatory and non-obligatory payment acceptance

	Logit (Odds Ratios)					
	Non-obligatory (1)	Obligatory (2)	Non-obligatory (3)	Obligatory (4)	Non-obligatory (5)	Obligatory (6)
Gender (female=1)	0.681*** (0.026)	0.615*** (0.068)	0.677*** (0.026)	0.618*** (0.069)	0.681*** (0.026)	0.615*** (0.068)
Years of practicing medicine in the U.S.	1.059*** (0.003)	1.060*** (0.006)	1.061*** (0.003)	1.060*** (0.006)	1.059*** (0.003)	1.060*** (0.006)
Control of Corruption	0.765*** (0.031)	1.318*** (0.132)	0.783*** (0.034)	1.390*** (0.150)	0.772*** (0.032)	1.309*** (0.132)
Hospital Policies	0.845*** (0.010)	0.941* (0.033)	0.541*** (0.026)	0.793* (0.094)	0.845*** (0.010)	0.941* (0.033)
Hospital Policy × Control of Corruption			0.921 (0.053)	0.813 (0.115)		
State Disclosure Policies	0.286*** (0.021)	0.591** (0.147)	0.325*** (0.025)	0.582** (0.143)	0.277*** (0.022)	0.596** (0.149)
State Disclosure Policies × Control of Corruption					0.896 (0.082)	1.155 (0.276)
Observations	13 304	13 304	13 304	13 304	13 304	13 304

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

The paper develops new hospital policy indices that control for obligatory and non-obligatory types of payments. For obligatory payment types, hospital policy index combines COI policies regarding consulting, speaker fees and travel and lodging. When investigating non-obligatory payments, COI policies of gift, educational material and food and beverage payments were combined (and respective z-scores were calculated). As can be seen in table 2.5, more

restrictive hospital policies seem to decrease the likelihood of acceptance of payments for both obligatory and non-obligatory payments, albeit obligatory payments decline less due to hospital policies than non-obligatory policies and are only significant at 10 percent level. Meanwhile, state disclosure policies are associated with lower likelihood and lower size of obligatory and non-obligatory accepted payments. The results indicate that physician behavior is affected by both country of origin's corruption norms and rules and regulations in the host country.

The results in table 2.5 also show that foreign-trained female physicians are less likely to accept obligatory and non-obligatory payments compared to their male colleagues. Thus, the hypothesis that women adopt more ethical behavior holds for both types of payments. Finally, with each year of practicing medicine, the likelihood of accepting both obligatory and non-obligatory payments increase. Such results are very intuitive, especially when studying the acceptance of obligatory payments. A physician's reputation, leadership role, academic and clinical achievements, and ability to influence other physicians' choices of treatments are desirable targets for the pharmaceutical industry.

Overall, the results in tables 2.1-2.5 have consistently shown that foreign-trained physicians tend to accept more in promotional payments with each additional year of practicing medicine. I next consider whether the differences in cultural background and acceptance of promotional payments change over the course of years of practicing medicine in the United States.

Table 2.6: Years of practicing medicine and control of corruption

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment >0 (2)	Interaction >0 (3)	Log Interaction >0 (4)
Control of Corruption	0.631*** (0.058)	0.416** (0.175)	0.631*** (0.058)	0.304*** (0.099)
Years of practicing medicine in the U.S.	1.067*** (0.004)	0.089*** (0.007)	1.067*** (0.004)	0.069*** (0.003)
Control of Corruption × Years of practicing medicine in the U.S.	0.987*** (0.005)	-0.057*** (0.008)	0.987*** (0.005)	-0.036*** (0.005)
Observations	12 984	7 358	12 984	7 358

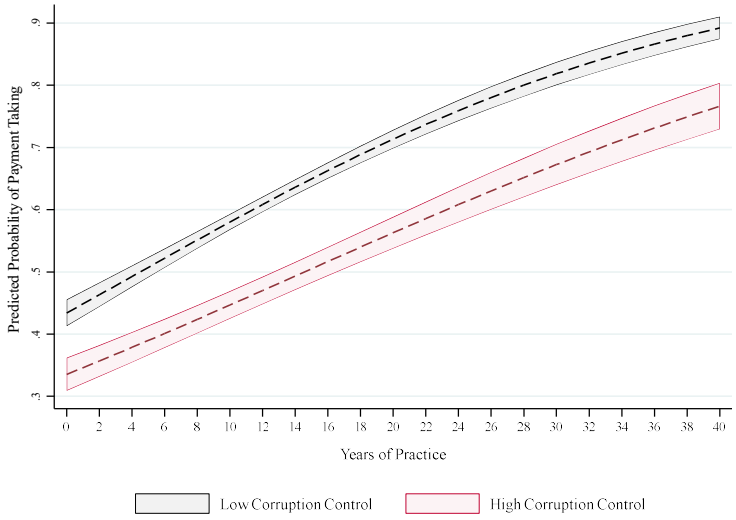
Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Barr and Serra's (2010) bribery experiment indicated that corruption levels in the country of origin was a good predictor of bribe acceptance among undergraduates. However, the study found that time spent in the host country (UK) was associated with a decline in the propensity to bribe. Table 2.6 explores changes in behavior over time by introducing an interaction term between control of corruption index and years of practicing medicine in the U.S. Column 2 indicates that, given that payments are positive, foreign-trained physicians on average accept more in promotional payments with each additional year of practicing medicine, everything else constant. One likely explanation is that physicians build stronger bonds with pharmaceutical industry representatives as they advance in their careers. It could also be the case that over time, experienced physicians build a reputation and become formal or informal leaders in their respective groups. A study by Weber and Ornstein (2010) argued that pharmaceutical companies

target leaders in physician groups that may help to increase the sale of prescription drugs. Thus, a physician's reputation, leadership role, academic and clinical achievements, and ability to influence other physicians' choices of treatments may be a desired target for pharmaceutical companies and may translate into higher promotional payments. Therefore, physicians who are in their mid-to-late careers are more likely to be hired as speakers and consultants by pharmaceutical companies.

Table 2.6 also shows that one unit increase in country of origin's control of corruption index (an improvement of country's corruption profile) is associated with lower likelihood of payment acceptance (column 1). Specifically, a unit increase in country of origin's control of corruption index is also associated with less (column 2) acceptance in promotional payments and fewer interactions with pharmaceutical sale representatives (column 4), everything else constant. For context, a physician from China would accept 5.7 percent less in promotional payments, than a physician from Myanmar; and a physician from Hungary would accept 5.7 percent less in promotional payments, than a physician from China (there is one unit difference in average control of corruption index between those countries).

Finally, table 2.6 provides insight into the relationship of country of origin's corruption norms and acceptance of promotional payments over time. With each additional year of practicing medicine in the U.S. foreign-trained physicians from more corrupt countries are more likely to accept promotional payments than their counterparts from less corrupt countries. The direction and significance of the finding can be seen in both table 2.6 and figure 2.5.



Notes: Estimates are from interaction term between variables years of practicing medicine and country of origin's control of corruption index, with all other variables described in equation 2.1 fixed at their sample means. Division at the median method was used, such that above median estimates of control of corruption are considered high control of corruption, while below median are considered low control of corruption.

Figure 2.5: Years of practicing medicine and control of corruption

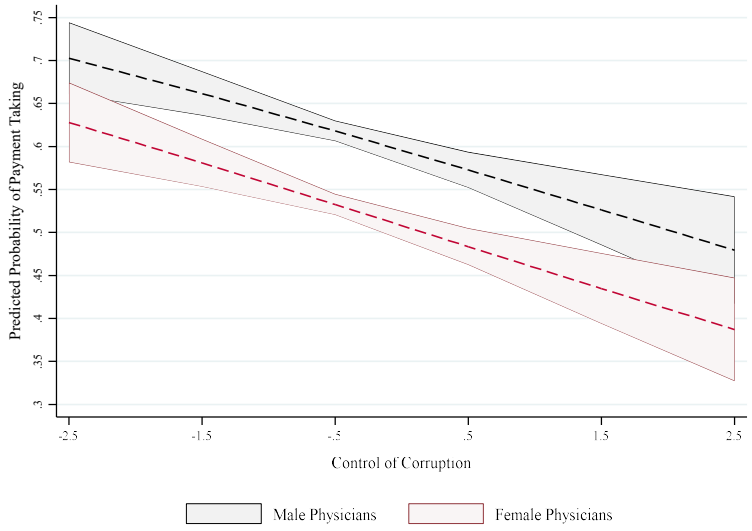
Perhaps sticky norms persist. One explanation offered by Smerdon, Oferman and Gneezy (2020) is that bad norms thrive and persist, because bad norm is an equilibrium of a coordination game. Another explanation for increased interactions and promotional payments stems from Jancsics (2014) work. Since corrupt deals are made secretly and have initially high potential transaction costs, repeated corrupt transactions automatically lead to a higher level of trust between the agent and the recipient. Such social institution structures the corrupt situation, stabilizes the prices for a particular action, and reduces the transaction costs of corruption (Della Porta and Vannucci, 2004). As a physician receives more opportunities for interactions with pharmaceutical industry and larger sized payments throughout years of practicing medicine in the U.S., the effect of corruption norms on a physician's behavior become more overt.

Finally, the paper examines the relationship and combined effect of a physician's gender and corruption norms. Although a physician's gender and improvement in country of origin's control of corruption index are associated with lower likelihood of accepted payments, the combination of gender and control of corruption is not statistically different from zero. Table 2.7 indicates that the likelihood and the size of payments are lower among female physicians compared to their male counterparts. It also shows that as country of origin's corruption index improves, physicians from those countries are less likely to accept payments from pharmaceutical industry. However, the likelihood of acceptance of payment is not statistically different among male and female physicians as country of origin's control of corruption improves by a unit (see figure 2.6 below).

Table 2.7: Physician's gender and control of corruption

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratio)	GLM	Logit (Odds Ratio)	GLM
	Payment >0 (1)	Log Payment >0 (2)	Interaction >0 (3)	Log Interaction >0 (4)
Control of Corruption	0.807*** (0.041)	0.011 (0.099)	0.807*** (0.041)	0.071 (0.048)
Female Physicians	0.667*** (0.028)	-0.264*** (0.0671)	0.667*** (0.028)	-0.303*** (0.043)
Female Physicians & Control of Corruption	0.990 (0.052)	-0.054 (0.067)	0.990 (0.052)	0.049 (0.053)
Observations	12 984	7 358	12 984	7 358

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$



Notes: Estimates are from interaction term between a physician's gender and country of origin's control of corruption index, with all other variables described in equation 2.1 fixed at their sample means.

Figure 2.6: Gender and control of corruption index

Robustness check

Two different robustness checks were conducted. In the first set of robustness checks (Appendix A) Grenada, Barbados, Sint Maarten, Antigua and Barbuda and Saint Kitts and Nevis were excluded from the sample. The reason for such exclusion rests on the fact that many medical schools in above mentioned areas are accredited. Foreign-trained physicians, who receive their initial training in such medical schools do not need to go through the same processes of certification as physicians from other countries and can more easily be admitted to the U.S. residencies. Randomly choosing and inspecting resumes of foreign-trained physicians from those universities revealed that some of them attended U.S. high schools and colleges,

before being admitted to medical universities in one of those places (thus, their country of origin is likely to be the U.S.)

Tables in Appendix A show that the direction and significance of results mostly stay unchanged when excluding Grenada, Barbados, Sint Maarten, Antigua and Barbuda and Saint Kitts and Nevis from the sample, leading to a conclusion that a foreign trained physician's behavior regarding payment acceptance from pharmaceutical industry is influenced both by corruption norms of the country of origin and host country's rules and regulations.

There are a few differences, however, between the regression results in Appendix A and regression results in the main text. The results of GLM model (columns 2 and 4) for control of corruption become statistically significant at 1 percent level in table A-1. When comparing the results for combined effect of control of corruption and hospital policies (tables 2.3 and A-2), country of origin's control of corruption is the only variable that changes its significance. In the main analysis, control of corruption is not statistically different from zero when using GLM model. When eliminating certain countries, however, the coefficient of control of corruption becomes statistically significant at 1 percent level. A similar outcome is observed when investigating the combined effect of hospital policies and country of origin's control of corruption index.

Some changes in significance of results for obligatory payments in table A-4, compared to those in tables 2.5 are also observed. Control of corruption is significant at 1 percent level when investigating obligatory payments in table 2.5 but becomes indistinguishable from 0 in table A-4. Meanwhile, hospital policies index is significant at 10 percent level when investigating obligatory payments in table 2.5 but is statistically indistinguishable from 0 in table A-4 (respective columns 1 and 2).

Finally, when comparing the combined effects of control of corruption and years of practicing medicine in the U.S., significance and magnitude in tables 2.6 and A-5 are fairly similar. There are a few differences, however, between results in the main regressions and the robustness check analysis. The interaction term of control of corruption and years of practicing medicine in the U.S. is statistically significant at 1 percent level when calculating the likelihood of accepting payments in table 2.6. Once certain countries are eliminated, the effect becomes statistically not different from 0. Meanwhile, the size of accepted payments for combined effect of control of corruption and years of practicing medicine, using the GLM model, is statistically significant at 5 percent level in table 2.6, while it is significant at 1 percent level in robustness check analysis (table A-5).

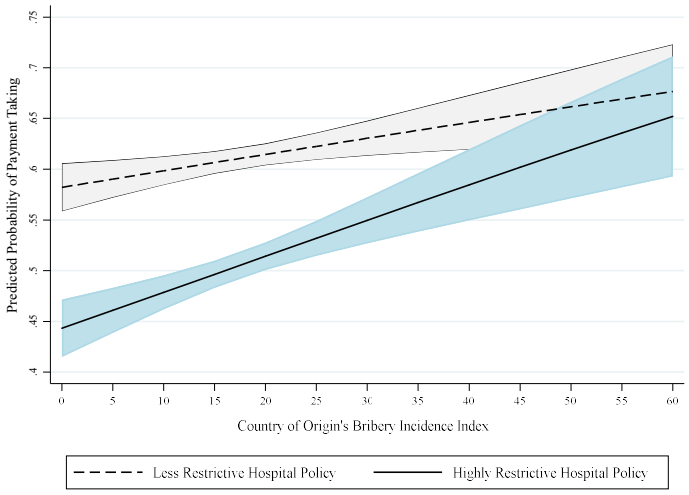
The second set of robustness checks uses different corruption indices. Bribery incidence and bribery depth indices are used to check if the relationships observed in the case of control of corruption index holds. Since the data of bribery depth and bribery incidence were not available for some countries in the sample, a multiple imputation method was used to calculate approximate values of missing data[21].

The results in Appendix B mostly reflect what is observed in the main regressions. There are a few differences, however. All corruption indices in table B-1 behave similarly to that of table 2.2, showing that 1 unit increase in country of origin's corruption index is associated with increased likelihood of accepting payments.

The relationship between country of origin's corruption norms and hospital policies in table B-2 have similar signs and significance as reported in table 2.3. However, the likelihood of

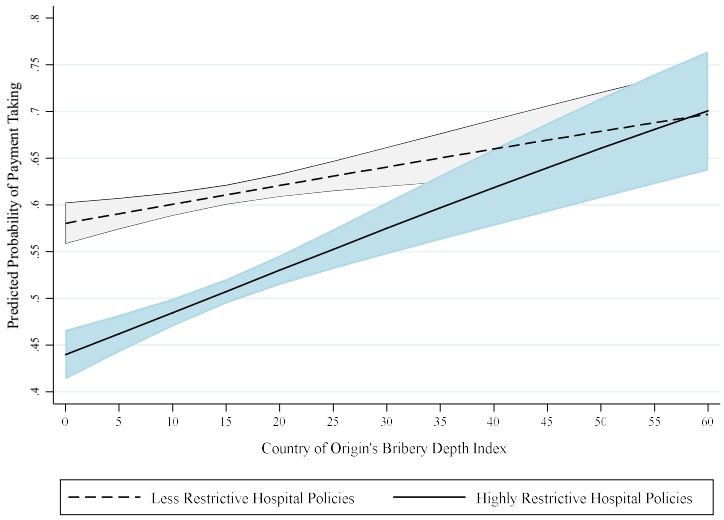
[21] Researchers usually address missing data by including in the analysis only complete (non-missing) cases. However, the results of such analyses can be biased. Multiple imputations is a flexible, simulation-based statistical technique for handling missing data. It creates several different plausible imputed data sets and appropriately combines results obtained from each of them (Sterne et al., 2009).

accepting payments in the robustness check analysis for combinations of both hospital policy index and bribery depth, and hospital policy index and bribery incidence are statistically significant at 1 percent level. In table 2.3, the combination of control of corruption and hospital policy index was not significantly different from 0. Figures 2.7 and 2.8 below show that restrictive hospital policies are more effective among foreign-trained physicians from less corrupt countries.



Notes: Estimates are from interaction term between variables country of origin's bribery incidence and hospital policy indices, with all other variables described in equation 2.1 fixed at their sample means. Highly restrictive hospital policy index mostly contains hospitals with stringent policies. Less restrictive hospital policy index, meanwhile, contains those with permissive and some moderate policies.

Figure 2.7: Hospital policies and bribery incidence



Notes: Estimates are from interaction term between variables country of origin's bribery depth and hospital policy indices, with all other variables described in equation 2.1 fixed at their sample means. Highly restrictive hospital policy index mostly contains hospitals with stringent policies. Less restrictive hospital policy index, meanwhile, contains those with permissive and some moderate policies.

Figure 2.8: Hospital policies and bribery depth

While the likelihood of accepting payments seems to be affected by the corruption norms of the country of origin and host country's rules and regulations, as tables B-2 and 2.3 show, such norms have no effect on the size of accepted payments.

The results in table B-3 are also somewhat similar to those in table 2.4. In table B-3 the coefficients on corruption indices and their interaction terms for likelihood of accepting payments (logit) and the size/elasticity of payments (GLM) are statistically significant at one percent level, unlike the coefficient of control of corruption and its interaction term that were statistically indistinguishable from zero. But more importantly, those results once again imply that in the presence of state policies, physicians from more corrupt countries tend to accept more in payments than those from less corrupt countries. When laws and regulations are in place, the

physicians from more law-abiding countries change their behavior and adopt to the requirements of state or hospital regulations. In other words, cultural background and behavior matter when discussing policies and regulations.

Some differences in results are also observed when comparing tables 2.5, B-4 and B-5. The results are similar in magnitude and significance when investigating non-obligatory payments. But, while the control of corruption coefficient was statistically significant at one percent level when investigating obligatory payments (columns 2,4,6 in table 2.5), bribery depth and bribery incidence indices are not significant in the robustness check analysis (columns 2,4,6 in tables B-4 and B-5). Meanwhile, the combination of state disclosure policies and bribery depth become statistically significant at one percent level when investigating non-obligatory payments in the robustness check analysis, while they were indistinguishable from zero in table 2.5. The coefficient of interaction term for hospital policies and corruption indices also become statistically significant at 10 percent level in robustness check analyses, while being indistinguishable from zero in table 2.5.

When investigating the combined effects of years of practicing medicine in the U.S. and corruption indices in table B-6, one may observe some differences comparing to the results in table 2.6. In table 2.6, both control of corruption and the interaction term were statistically significant at one percent level. In the robustness check analysis, the interaction terms are significant at one percent level as in table 2.6, but the corruption indices are indistinguishable from zero.

The results in tables A-6 and B-7 are largely like those in table 2.7. One departure, however, is that in table 2.7 the interaction term of gender and control of corruption is not statistically different from zero when using both Logit and GLM models. In the robustness check

analyses, the interaction term is significant at 5 percent level when using Logit model in table B-7. The interaction term is also significant at 5 percent level when using GLM model (both in tables A-6 and B-7), showing that as country of origin's corruption index increases the size of accepted payments increase more among women from corrupt countries compared to the reference group.

Finally, corruption norms may be linked to and simply be proxies for countries' GDP per capita PPP. To test the validity of the results and ensure that outcomes are not driven simply by GDP per capita PPP, in Appendix C, along with correlation table, I report the regression results excluding GDP per capita PPP. The result mostly obtain with and without control for GDP per capita.

Overall, the results in Appendix A, B and C largely match the results in tables 2.2-2.7, confirming that country of origin's cultural norms affect foreign-trained physicians' behavior in the host country. Analyses showed that physicians from less corrupt countries tend to adopt and abide to the rules and regulations in the host country more eagerly than their counterparts from more corrupt countries.

2.5. Conclusion

This paper examined the differences in attitude towards pharmaceutical promotions among foreign trained internal medicine doctors. It found a negative relationship between state disclosure policies and acceptance of payments from pharmaceutical industry. Foreign trained physicians, who practice medicine in one of the states that adopted disclosure policies prior to the Sunshine Act, on average accept less in promotional payments than physicians who practice

medicine in the rest of the country. The study emphasized that physicians from less corrupt countries change their payment acceptance and interaction behavior more when laws and regulations are in place. It showed that state disclosure policies have a larger effect on physicians from less corrupt countries, where laws are more reinforced, and people tend to be more law abiding. Cultural background becomes an important factor predicting the behavior when regulations are in place.

The study also showed that the likelihood of payment acceptance and frequency of interactions is less among those foreign-trained physicians who work at the hospitals with more restrictive policies. Restrictive hospital policies affect the behavior of especially those physicians from less corrupt countries. One likely explanation is that citizens are law abiding in less corrupt countries and grow up following laws and regulations. Once they are exposed to more restrictive hospital rules in the host country, they follow the rules more eagerly and change their behavior accordingly. On the contrary, hospital policies seem to be less effective among physicians from more corrupt countries.

The related third finding is a positive relationship between time spent practicing medicine (years in practice) and acceptance of promotional payments. This is consistent with the Alssageer and Kowalski (2012) findings that physicians practicing for more than 10 years were more than three times as likely as those having 1–3 years of practice to meet a pharmaceutical sales representative at least once a week. The paper also showed that with each additional year of practicing medicine in the U.S., physicians from more corrupt countries accept more in promotional payments compared to colleagues from less corrupt countries. This finding contradicts Barr and Serra's (2010) bribery experiment showing that time spent in the host

country was associated with a decline in propensity to bribe among all Oxford University students.

Alssageer and Kowalski (2012) indicated that male physicians are visited by pharmaceutical representatives more than female physicians. The analyses in this paper confirm their findings, showing that there is a strong negative association between gender and propensity of promotional payment acceptance. Female physicians tend to accept less in promotional payments and interact less with pharmaceutical representative than their male colleagues. Overall, this study indicated that physician gender and background matter and should be carefully considered when developing and implementing policies aiming to reduce pharmaceutical industry-physician financial interactions.

More importantly, the study showed that receiving medical training in a more corrupt country is associated with higher propensity of accepting promotional payments and more frequent interactions with pharmaceutical industry representatives. Although morality or the decision to be ethical is a phenomenon that can be partially affected through time by both factors intrinsic and extrinsic to the individual, morality and cultural norms seem to persist. The results are consistent with Fisman and Miguel's (2007) findings of strong persistence in corruption norms. Analysis of the nature of payments revealed that foreign trained physicians from less corrupt countries are less likely to accept non-obligatory payments (such as food and beverage, educational and gift-related payments), but are more likely to accept obligatory payments (such as speaker fees, consulting and travel and lodging-related payments) compared to their counterparts from more corrupt countries.

Physician–pharmaceutical industry interactions have been found to affect physicians' prescribing behavior and contribute to irrational prescribing of the company's drug (Wall and

Brown, 2007; Othman et al., 2010; Wazana, 2000; Fickweiler, Fickweiler and Urbach, 2017). Hence, policy interventions and education about the implications of these interactions is needed. Given the findings in this study, I recommend:

1) Including ethical trainings not only in medical school, but also residency and fellowship curricula.

1) Designing ethical trainings considering different cultural backgrounds and variation in perception of wrongdoing.

3) Adopting more stringent conflict of interest policies in hospitals.

CHAPTER 3: DO MEDICAL SCHOOL ETHICS POLICIES AFFECT THE RELATIONSHIP BETWEEN BIG PHARMA AND PHYSICIANS?

3.1 Introduction

The pharmaceutical industry spends billions of dollars annually on providing gifts, samples, trips, honoraria, consulting and speaker fees to physicians. Such promotions come with a cost to the general population in the form of increased drug expenditures (King and Bearman, 2017). Pharmaceutical promotions tend to influence physicians' choice of treatments (Yeh et al., 2016; Perlis and Perlis, 2016), even if equivalent low-priced products are available (Akande and Aderibigbe, 2007).

Pharmaceutical promotions are prominent in most medical schools and teaching hospitals (Lurie, Rich and Simpson, 1990; Bellin, et al., 2004; Sigworth, Nettleman and Cohen, 2001). A survey conducted in Finland showed that medical students frequently attend presentations by pharmaceutical sales representatives, with 44 percent of students participating in such presentations at least twice a month (Vuorenkoski, Valta and Helve, 2008). Medical students in the U.S. also report attending events sponsored by pharmaceutical companies and receiving gifts from them (Burashnikova, Ziganshin and Ziganshina, 2008; Zipkin and Steinman, 2005). Such promotions can have both short- and long-term effects on physician prescribing. The exposure to the pharmaceutical industry may communicate a message encouraging overuse of certain drugs (Austad, Avorn and Kesselheim, 2011). A study by Vainiomäki, Helve and Vuorenkoski (2004) argued that medical students consider the pharmaceutical industry as one of their most important sources of drug information and believe that promotional activities may affect their future

prescribing behavior. It has been noted that the pharmaceutical industry–physician interactions that begin in medical school, often continue into residency and practice (Wazana, 2000).

Realizing the effect of industry relationship on future prescribing habits of physicians, some medical schools implemented policies forbidding interactions between students and faculty with pharmaceutical sales representatives. Using a dataset that describes the nature of interactions between pharmaceutical companies and physicians, this chapter examines the effect of medical school policies on the likelihood and size of promotional payment acceptance later in physicians' careers. It discusses the physician-pharmaceutical sales representative's financial relationships among family medicine doctors who graduated from 134 U.S. medical schools and shows that medical school policies affect physician's propensity to accept payments later in their career. Restrictive medical school meal policies and acceptance of food and beverage-related payments seem to be especially effective in reducing interactions. The study also argues that physician's gender, length of practicing medicine, and the size of practice affect promotional payment acceptance.

This work contributes to a growing literature concerning medical school policies and physician-pharmaceutical industry relationships (King et al., 2013; Grande et al., 2009; Zipkin and Steinman, 2005; Vainiomäki, Helve and Vuorenkoski, 2004). The findings offer insights into the behavior of physicians, and factors that affect the likelihood and size of accepted promotional payments.

The rest of the chapter is structured as follows: section 3.2 discusses the literature of gift acceptance among medical students and residents, section 3.3 describes the data, section 3.4 discusses the empirical strategy and results, and section 3.5 concludes.

3.2 Literature Review

Pharmaceutical companies spend, on average, twice as much on marketing to physicians and the public as they do on research and development (Zipkin and Steinman, 2005; Mahan, 2002; Collier, 2009). Every year, pharmaceutical companies sponsor hundreds of thousands of events and give gifts to physicians in their efforts to influence physician prescribing and increase prescription sales (Morrison, 2000).

Since medical students, residents and fellows form preferences and practice patterns early in their careers, they are typically targeted by pharmaceutical companies while at school and when they are particularly vulnerable to the effects of industry promotions. Studies have shown that most medical students report receiving gifts from pharmaceutical companies, attending sponsored meals, conferences, and scientific meetings (Burashnikova, Ziganshin and Ziganshina, 2008; Zipkin and Steinman, 2005; Vainiomäki, Helve and Vuorenkoski, 2004). Pharmaceutical companies do not necessarily give expensive gifts or talks to influence medical trainees. Small gifts, such as pens, coffee mugs that display a pharmaceutical company's logo or other branded materials strengthen brand awareness, build brand equity through a variety of largely unconscious but powerful mechanisms (Grande et al., 2009).

A survey conducted by Fitz el al. (2007) revealed that 65 percent of clinical students and 28 percent of pre-clinical students believed accepting gifts from pharmaceutical industry was appropriate. Sandberg et al. (1997) argue that 90 percent of medical students receive at least one book from a drug company. Other studies have shown that residents in internal medicine and psychiatry attend between one and one-half and eight industry-sponsored lunches or rounds a month (Hodges, 1995; Brotzman and Mark, 1993), while emergency medicine residents interact

with pharmaceutical representatives one to three times per week (Reeder, Dougherty and White, 1993). Keim, Mays and Grant (2004), Lichstein, Turner and O'Brien, (1992) note that pharmaceutical sales representatives are allowed to give presentations in roughly half of internal medicine and emergency medicine programs in the U.S.

The interactions between medical students, residents and pharmaceutical sales representatives may affect more than just individual prescribing decisions. Standards of behavior toward industry representatives are learned in training and shape the professional values of future physicians. From the beginning of training, most physicians observe their colleagues and mentors receiving a wide variety of gifts. In such environment, medical students and residents are less likely to think critically about promotions. As a result, medical students and residents may hold generally positive attitudes toward gifts from industry, believing they are not influenced by them (Steinman, Shlipak and McPhee, 2001). Sarikaya, Civaner and Vatansever (2009) argue that deliberate targeting of medical students by pharmaceutical sales representatives is correlated with being less sensitive to the negative effects of marketing and leads to developing positive opinions about interactions with pharmaceutical companies. Additionally, even when medical students genuinely believe that gifts are inappropriate, as Keim et al. (1993) have shown, they still accept them and perceive that they are entitled to gifts based on hardship.

The relationship between the pharmaceutical industry and trainees may have both short- and long-term negative effects. Visits and gifts from pharmaceutical representatives are designed to increase prescription sales for specific products (Morrison, 2000), create brand loyalty and cultivate subconscious commercial relationships with prescribers (Williams, 2003). They may create conflict of interest. Provision of promotional gifts can be seen as a friendship building technique designed to reinforce the communication between pharmaceutical representatives and

physicians (Katz, Caplan and Merz, 2003). It has also been argued that interactions with pharmaceutical sales representatives and drug detailing is a major source of drug information for physicians (Caudill, Lurie and Rich, 1992). Studies have shown that physicians have confidence that pharmaceutical promotions are a useful and a convenient source of medical information (Al-Areefi, Hassali and Mohamed Ibrahim, 2013; Kerak, Louhoudi and Ouardouz, 2014).

Pharmaceutical sales representatives, however, are not always a source for accurate information. They tend to present only selected, usually positive, information about their products (Lexchin, 1997). A survey of 255 physicians from Canada, US and France showed that minimally adequate safety information, including serious adverse effects was mentioned only in 1.7 percent of visits, even though 45 percent of medications presented during those meeting had FDA "black box" warnings. Despite this, in 54 percent of the cases the information provided by pharmaceutical sales representatives was thought to be good to excellent and 64 percent of time physicians indicated readiness to prescribe the medication (Mintzes et al., 2013). Overall, interactions between pharmaceutical companies and medical professionals may lead to irrational use of medicine and negatively affect the patient–physician relationship (Sarikaya, Civaner and Vatansever, 2009). The relationship can also create a sense of entitlement and erode professional values (George Washington University, 2009), lead to prescribing bias and other long-term effects.

Over the past two-three decades concerns have been raised about the ethical dilemmas surrounding physician–industry interactions. Several professional organizations including the American Medical Association (AMA) established written guidelines in the 1990's regarding the appropriateness of accepting gifts from pharmaceutical sales representatives. The AMA considered gifts to physicians acceptable as long as they were of minimal value and entailed a

benefit to patients (American Medical Association, 1993). Some medical students rallied for a more rigorous code of ethics and in 2002 American Medical Student Association (AMSA) established a set of guidelines urging all medical students and physicians to refuse all gifts and adopt a policy prohibiting pharmaceutical advertisements in AMSA publications (American Medical Student Association, 2003). The need for more rigorous gift policies can be seen in the Grande et al. (2009) experiment showing that exposure to small pharmaceutical promotional items influences medical students' inclination toward marketed products. The study compared medical students' attitude towards pharmaceutical promotional items at University of Pennsylvania School of Medicine (a school with restrictive policies prohibiting gifts, meals, and samples) and the University of Miami Miller School of Medicine (a school with no such policies) and found that University of Pennsylvania medical students exhibited a negative response towards a certain drug after receiving branded items, while students from Miami responded positively towards the branded drug. A study by Brotzman and Mark (1993) showed that graduates of residency programs that restrict exposure to pharmaceutical representatives have more skeptical attitude towards pharmaceutical promotional efforts than residents from programs with more permissive policies. Today, many medical schools and teaching hospitals continue accepting promotional payments from pharmaceutical and medical device manufacturers.

There are competing views on medical school policies and payments acceptance later in a physician's career. McCormick et al. (2001) and Ferguson at al. (1999) examined the long-term effects of residency policies. Both studies showed that physicians who graduated from programs with or without restrictive policies were equally likely to interact with pharmaceutical sales representatives and accept samples. However, McCormick et al. (2001) also found that

interactions with pharmaceutical sales representatives were less "intense" among graduates exposed to more restrictive vendor relationship policies during residency.

On the contrary, a study of 14 U.S. medical schools found that physicians, who were exposed to gift restriction policies during medical school, prescribed a newly introduced stimulant and antipsychotic significantly less than older alternatives. Prescribing rates for new antipsychotic drugs were further reduced among physicians who were exposed to gift restriction policies longer or who experienced more stringent policies (King et al., 2013). Meanwhile, investigating the behavior of 1,652 psychiatrists from 162 residency programs, Epstein et al. (2013) also found that policies prohibiting pharmaceutical industry interactions in residency programs result in prescribing behavior that appear to be less influenced by pharmaceutical companies.

This chapter considers whether medical school policies affect the likelihood and size of promotional payments acceptance later in the careers of family medicine doctors. It also considers whether medical school policies are more effective in terms of reducing interactions with pharmaceutical industry. The work is part of a growing body of research on the importance of policies in explaining individual behavior.

3.3 Data

Most physicians receive gifts from the pharmaceutical industry in the form of small samples, books, and free meals. But some also receive more expensive gifts, such as travel to a conference or tickets to entertainment events (Madhavan et al., 1997). I use Open Payments 2014-2018 data to track individual promotional payments. The dataset provides detailed information on the date and size of a payment to each family medicine doctor from

pharmaceutical providers, the nature of the payment[22] (e.g., food, speaker fees, travel, etc.) and number of interactions between a physician and pharmaceutical sales representatives[23]. As was explained in chapters one and two, zero payments were added to the data for those cases when physicians did not accept payments from pharmaceutical companies.

The CMS National Provider Identifier File (NPIF) was used to obtain physician background information. CMS NPIF provides information about physician characteristics including provider name, specialty code(s), provider's gender, attended U.S. medical school, year of graduation and number of group members in a physician practice. The sample consists of 1,839 family medicine doctors and constitutes for four percent of all U.S.-trained family medicine doctors. The study is limited to family medicine doctors for two reasons:

(1) family medicine doctors tend to work in small physician practices, that do not have formal gift acceptance policies. Therefore, the paper does not need to control for policies of promotional payment acceptance at the workplace;

(2) primary care specialties (such as family medicine) have the shortest residency programs. While ethics and norms in residency programs may affect future behavior of promotional payment acceptance, the less time a physician spends in a residency program, the less they are exposed to the policies of a residency program.

The study is further limited to physicians who work in groups of less than 25 physicians. Such groups are less likely to adopt formal Conflict of Interest policies (Cascardo, 2009). Additionally, medium- and big-sized physician practices are typically located in more populous areas and can be more desired targets for pharmaceutical sales representatives than small

[22] Payments related to royalties, ownership, dividends, and charities are excluded from the sample because of their non-marketing nature.

[23] Drug samples are not included in the study, since Open Payments database does not record samples of drugs provided to physicians by pharmaceutical sales representatives.

physician practices. Meanwhile, in small practices exchange of knowledge between physicians occurs at much lower rate. In such cases, physicians need to rely more heavily on pharmaceutical sales representatives as a source of medical information. I divide physician practices into two groups: a small physician practice with less than 5 physicians and a medium sized group with 6-25 physicians.

The paper examines how medical school policies affect the likelihood and size of accepted promotional payments later in a physician's career. The data on medical school policies was hand-collected from sources such as Institute on Medicine as a Profession and respective medical schools' Conflict of Interests handbooks.

Many medical schools developed and implemented Conflict of Interest policies addressing the relationship between the faculty, medical students, and pharmaceutical sales representatives only recently. Information on dates of latest policy adoption and modification was also hand collected, thus allowing for differentiation between physicians who were exposed and those who were not exposed to medical school policies.

The paper is limited to those physicians who started practicing medicine between 2002 and 2011. The period was chosen for two main reasons:

a) many medical schools changed their vendor relation, meal, and gift policies after 2002. Specifically, 99 out of 134 medical schools in the sample changed their policies between 2008 and 2011. This range allows one to build control and treatment groups of physicians who were exposed and not exposed to policy changes.

b) The length of practicing medicine among physicians in the treatment and control groups is similar (0-13 years).

Conflict of Interest (COI) policies that regulate pharmaceutical industry-medical student relations are labelled as 1) permissive policies (no restrictions on how much can be accepted in a certain type of payment), 2) moderate policies (an upper limit[24] is set by a medical school with regards to acceptance of certain types of payments), 3) stringent policies (interactions and payments are highly limited or not allowed at all).

I explore the effect of medical school meal policies on meal-related payments later in a physician's career, as well as the effect of both gift and meal policies on all types of payments[25]. A medical school policy index was constructed by combining gift and meal policies and calculating its z scores. To calculate the effect of restrictive policies on payment acceptance, a highly restrictive and less restrictive medical school policy index was also developed by using a division at the median method. It should be noted, however, that the study is limited to the official medical school policies and cannot claim anything about the implementation of COI policies. One of the limitations of this study is not controlling for residency program policies.

The study also examines the relationships between the size and frequency of promotional payments, gender, and tenure of practicing medicine. Finally, it examines payments by states. As was explained in chapters one and two, prior to adoption of the Sunshine Act, few states already banned gifts or required disclosure of gifts from pharmaceutical companies. The study exploits such geographic variation to analyze the relationship between medical school policies, disclosure policies, and promotional payments to family medicine doctors.

[24] The upper limit may vary depending on the type of payment.

[25] Those are two policies that directly regulate the relations between medical students and pharmaceutical sales representatives.

Table 3.1: Descriptive statistics

	Size of Payments		Frequency of payments		
	Mean	Standard Deviation	Mean	Standard Deviation	N
Payments	322.93	567.94	23.81	45.82	8 655
Payments to male physician	414.29	647.12	31.13	52.95	4 035
Payments to female physician	243.14	474.27	17.42	37.37	4 620
Payments by years of practicing medicine					
Payments in early career (<5 years)	252.36	475.82	17.97	37.00	2 509
Payments in mid-career (5 - 10 years)	347.51	593.75	25.82	48.26	5 056
Payments in late career (10+ years)	371.36	623.51	27.92	51.02	1 090
Overall payments by medical school meal policies					
Permissive medical school meal policies	364.90	578.43	27.12	46.61	1 310
Moderate medical school meal policies	326.28	577.51	23.36	46.13	2 890
Stringent medical school meal policies	308.41	557.96	23.13	45.35	4 455
Overall payments by medical school gift policies					
Permissive medical school education and gift policies	238.91	476.97	17.56	38.79	1 140
Moderate medical school education and gift policies	382.47	610.21	28.37	49.31	4 185
Stringent medical school education and gift policies	276.86	532.61	20.23	42.83	3 330
Payments when exposed to policies					
Payments when exposed to policy change	355.13	549.95	25.84	43.04	945
Payments when not exposed to policy change	318.98	570.01	23.56	46.14	7 710
Payments by state policies					
Payments to physicians practicing in states adopted disclosure policies prior to Sunshine Act	110.54	423.34	8.79	35.29	505

Payments to physicians practicing in states did not adopt disclosure policies prior to Sunshine Act	336.09	573.14	24.74	46.23	8 150
Payments by physician practice size					
Physician practice size (<=5)	424.45	647.31	29.84	48.74	2 665
Physician practice size (6-25)	277.76	522.57	21.13	44.19	5 990

Table 3.1 contains descriptive statistics regarding overall size and frequency of payments, payments regarding different policies, and payments by length of practice and practice size.

Figure 3.1 indicates that food and beverage-related payments constitute 73 percent of overall accepted payments (as well as 98 percent of all interactions between physicians and pharmaceutical sales representative) in the sample. While I analyze overall payments, I concentrate on food and beverage-related payments given the size and importance of those payments in pharmaceutical-physician relations.

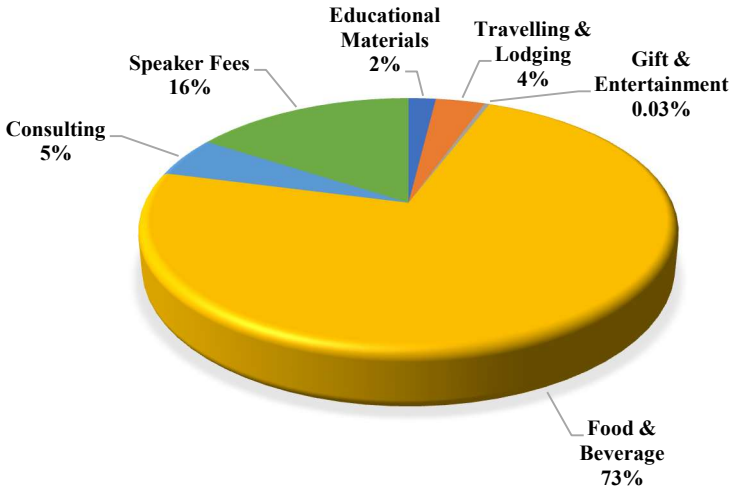


Figure 3.1: Types of payments

3.4 Empirical Strategy and Results

My primary empirical strategy explores the differences in accepting promotional payments by physicians based on medical school policies, gender, tenure and other characteristics. A large percentage of physicians did not accept any promotional payment, resulting in large mass point at zero and positive values (figure 3.2).

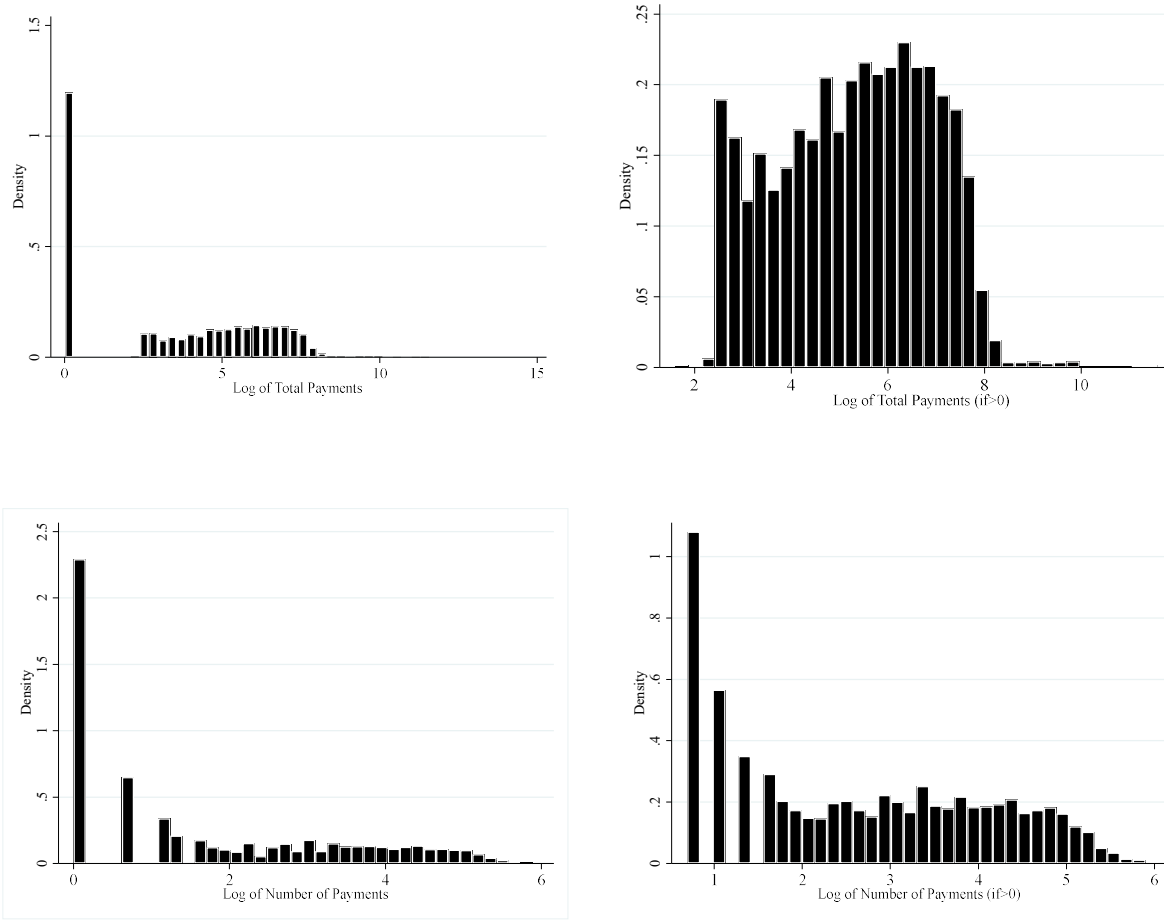


Figure 3.2: The size and frequency of payments

Using two separate models for the likelihood of payment acceptance and how much to accept given a decision to accept a payment seems to be the best empirical approach given the data[26]. The probability of observing a positive-versus-zero payment is measured using the Logit model. Then, conditional on a positive payment, an appropriate regression model is chosen. The choice of second model depends on the characteristics of the dependent variable. This chapter utilizes the GLM model.

I also bootstrap standard errors for predicted means. The bootstrap is a statistical procedure that resamples the dataset to create many simulated samples (Deb, Norton and Manning, 2017). Calculations are conducted in each of the bootstrap samples and estimates from those samples are used to approximate the distribution.

Since the data contain outliers that may dominate the analysis and produce results that do not reflect the central tendency well, I also use quantile regression model for positive values of the dependent variable. Quantile regression model allows investigation of relationships which are resistant to outliers. They are also useful in understanding outcomes that are non-normally distributed and that have nonlinear relationships with explanatory variables (Lê Cook and Manning, 2013).

Specification Tests for GLM

As in chapters one and two, this study too utilizes Box-Cox test to examine what power function will transform the dependent variable, total payments to physicians, to be closest to symmetric. The natural log transformation was found to be the best fit.

[26] As explained in chapters one and two, neither the standard Tobit model nor Heckman selection models are appropriate in this context.

Next, modified Park test (Park, 1966) was performed to determine the distribution family, that is, the relationship between the mean and the variance. Deb, Norton and Manning (2017) explain that the Gaussian distribution should be used when the coefficient of the expected value is close to 0, a Poisson-type distribution when the coefficient is close to 1, the Gamma distribution when the coefficient is close to 2 and the inverse-Gaussian distribution when the coefficient is close to 3. The estimated coefficient of 1.66 supports the use of gamma distribution.

Model specification

The dependent variable in the main econometric specification is total payments accepted by physician i who graduated from medical school j and practices medicine in the state k ($TotalPayments_{ijk}$). Figure 3.2 indicates that frequency of payments can also be treated as continuous variable and used in the same manner.

As in chapter two, I use two different models to calculate the probability and the size of accepted payments. The first model examines the likelihood of accepting payment. Independent variables include physician's gender, medical school policies, whether a physician was exposed to medical school policy changes, length of practicing medicine and physician-related other characteristics.

$$\Pr(TotalPayments_{ijk} > 0) = \nu_0 + \nu_1 YearsInPractice_i + \nu_2 MedSchoolPolicies_{ij} + \nu_3 ExposedtoPolicies_{ij} + \nu_4 PhysicianGender_i + \nu_5 Size_i + \nu_6 State_k + \nu_7 YearEffects_{ijk} \quad (3.1)$$

where, $YearsInPractice_i$ is the length of practicing medicine (in years) by physician i, $MedSchoolPolicies_{ij}$ is medical school j Conflict of Interest policy index that physician i attended, $ExposedtoPolicies_{ij}$ determines whether physician i was exposed to medical school j's Conflict of Interest policy changes, $PhysicianGender_i$ is a dummy variable that assigns a value of 1 to a female physician, $Size_i$ is a dummy variable that assumes a value of 1 when physician i's practice has a size of more than 5 physicians, $State_k$is dummy variable that indicates whether state k where a physician practices medicine adopted disclosure policies prior to Sunshine Act, and $YearEffects_{ijk}$ include year fixed effects of 2014-2018.

The study also investigates the combined effect of medical school policies and exposure to those policies. Since the paper follows individual physicians practicing medicine, it is important to examine the related question of whether there is any evolution of behavior. This study interacts a medical school policy index and years of practicing medicine to track the change in behavior across family medicine doctors.

The second model examines the size of the payments for physicians who accept payments using the independent variables identified above. The equation of interest is the following:

$$\mathrm{E}(\mathrm{Log}(TotalPayments_{ijk}) \,|\, TotalPayments_{ijk} > 0) = g^{-1}(\beta_0 + \beta_1 YearsInPractice_i + \beta_2 MedSchoolPolicies_{ij} + \beta_3 EExposedtoPolicies_{ij} + \beta_4 PhysicianGender_i + \beta_5 Size_i + \beta_6 State_k + \beta_7 YearEffects_{ijk}) \qquad (3.2)$$

where g^{-1} is the link function in the GLM model. Note that (3.1) and (3.2) do not make any assumption about the correlation between the errors of equations (1) and (2). They do not need to be independent to get consistent estimates of the parameters ν and β.

Results

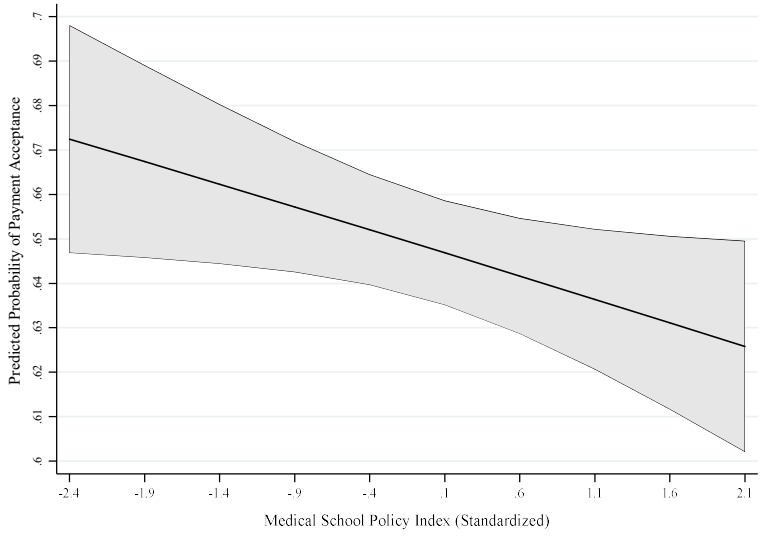
In the analyses presented below both size of payments (total payments) and frequency of payments were used as dependent variables. Logistic model results are reported in odds ratios and show the likelihood of accepting any payment or having any interaction with pharmaceutical sales representatives in the period of observation. Following Mooney and Duval (1993), standard errors were bootstrapped using 50 replications.

Table 3.2: All types of payments

	Total Payments						Frequency of Payments	
	Logit (Odd Ratios)	GLM	Quantile Regressions				Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment >0 (2)	25th Percentile (3)	50th Percentile (4)	75th Percentile (5)	90th Percentile (6)	Payment >0 (7)	Log Payment >0 (8)
Medical School Policy Index	0.953* (0.024)	-0.070* (0.038)	-3.016 (2.039)	-25.733*** (6.441)	-75.602*** (15.241)	-34.693 (26.667)	0.953** (0.021)	-0.044* (0.024)
Exposed to Policies	1.736*** (0.135)	0.131* (0.075)	17.900*** (6.120)	48.582*** (13.666)	240.607*** (52.150)	20.700 (82.760)	1.736*** (0.136)	0.201*** (0.055)
Female physician	0.618*** (0.029)	-0.395*** (0.069)	-21.538*** (5.087)	-107.798*** (12.515)	-294.913*** (34.299)	-442.004*** (70.655)	0.618*** (0.028)	-0.378*** (0.031)
Years in practice	1.053*** (0.010)	0.102*** (0.012)	3.133*** (0.908)	18.207*** (2.049)	52.060*** (6.282)	67.956*** (12.465)	1.053*** (0.010)	0.067*** (0.007)
State adopted disclosure policies prior to Sunshine Act	0.281*** (0.023)	-0.377** (0.182)	-25.840*** (4.694)	-123.128*** (13.699)	-284.140*** (68.332)	-64.666 (333.899)	0.281*** (0.030)	-0.170 (0.172)
Size of Physician Practice (<=5, 6-25)	0.641*** (0.034)	-0.458*** (0.073)	-20.410*** (5.156)	-98.466*** (10.609)	-233.317*** (37.154)	-331.977*** (61.773)	0.641*** (0.036)	-0.136*** (0.038)
Observations	8 657	5 608	5 608	5 608	5 608	5 608	8 657	5 608

Notes: All models include years fixed effects. Bootstrapped standard errors in parentheses, $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

The results in table 3.2 suggest that medical school policies affect both the likelihood and the size of accepted payments (columns 1 and 2). Figure 3.3 below shows the relationship between medical school policies and the likelihood of payment acceptance. The effect of medical school policies on payment acceptance is especially evident at the median and 75th percentiles. The results suggest that at the median a one unit increase in medical school policy index (becoming more restrictive) is associated with 25.7 fewer dollars accepted per physician payment, everything else constant. Medical school policies also affect the frequency of interactions with pharmaceutical sales representatives (columns 7 and 8) indicating that physicians who attended medical school policies with more restrictive policies are less likely to interact and have fewer interactions with pharmaceutical sale representatives compared with those who attended medical schools with less restrictive policies. A unit increase in the medical school policy index is associated with 4.7 reduction in the frequency of payments.



Notes: Estimates are from equation 3.1 with all other variables fixed at their sample means.

Figure 3.3: Medical school policies

Meanwhile, larger physician practice size is associated with lower likelihood (columns 1 and 7) and lower size of promotional payment acceptance (columns 2-6 and 8). On one hand larger practices might be located in more densely populated areas and therefore be more desirable targets for pharmaceutical promotions. Larger practices can attract more clientele and have higher potential to boost brand-name drug prescriptions. Therefore, the expenditures for promoting a drug in larger practice is expected to be higher with more frequent visits to the practice by pharmaceutical sales representatives. On the other hand, in larger physician practices the value of promotional payments would be divided among more physicians, leading to lower sized payments and lower frequency of interactions per physician. For instance, if a pharmaceutical sales representative visits an office of a single-physician practice twice bringing coffee and doughnuts of value 25 dollars each time, it will be reflected in the database as two visits per physician with 50 dollars in total promotional payments. Meanwhile, if the pharmaceutical sales representative visits a two-physician practice twice with coffee and doughnuts of value 25 dollars each time, such visits will be reflected in the database as 25 dollars in total promotional payments per physician (each visit being 12.5 dollars per physician). Thus, even though larger physician practices are more attractive in terms of promotions and are time and cost effective for pharmaceutical sales representatives, more frequent visits to the practice and larger sized promotional payments will be divided between more physicians in the practice, leading to lower payments and visits per physician. Meanwhile, in small practices physicians do not have sufficient free time to keep up with medical literature. Spillover of knowledge from physician to physician may also occur at a much lower rate in small practices. In such cases, physicians need to rely more heavily on pharmaceutical sales representatives as a source of medical information and interact more frequently with them to obtain samples of the drugs and

information about new treatments. On the contrary, in larger physician practices information is transferred not only from pharmaceutical representative to physician, but also from physician to physician. Information about new treatments may be obtained from medical literature, from peers and other sources, leading to less reliance on pharmaceutical representatives as primary source of information and thus, less interactions.

Female physicians are less likely to accept payments and interact with pharmaceutical sales representatives than their male counterparts according to results in table 3.2. Female physicians on average accept 39.5 percent less in promotional payments and interact 37.8 percent less with pharmaceutical sales representatives than their male colleagues, given that payments and interactions are positive. The median regression results suggest that female physicians accept 107.8 dollars less in promotional payments compared with their male colleagues, other things constant.

The results also indicate that frequency of interactions and the size of accepted payments from pharmaceutical companies seem to increase with tenure. As physicians practice medicine for longer periods of time, assume leadership roles in their groups and establish relationships with pharmaceutical industry, they are more likely to be approached aggressively by pharmaceutical sales representatives and be offered larger sized payments. Columns 2 and 8 reveal that each additional year of practicing medicine is associated with a 10 percent increase in accepted promotional payments and a 6.7 percent increase in interactions with pharmaceutical representatives, given that payments and interactions are positive.

Finally, table 3.2 suggests that physicians who practice in states that adopted disclosure policies prior to Sunshine Act, are less likely to accept promotional payments compared to their counterparts. Physicians practicing in states that adopted disclosure policies prior to Sunshine

Act, are also less likely to interact with pharmaceutical sales representatives as compared with those who practice in the states that did not adopt such policies.

Table 3.3: Exposure to medical school policies, all payments

	Total Payments						Frequency of Payments	
	Logit	GLM	Quantile Regressions				Logit	GLM
	Payment >0 (1)	Log Payment >0 (2)	25th Percentile (3)	50th Percentile (4)	75th Percentile (5)	90th Percentile (6)	Payment >0 (7)	Log Payment >0 (8)
More Restrictive Medical School Policies	0.862***	-0.121	-6.795	-48.380***	-184.170***	-202.590***	0.862**	-0.119**
	(0.040)	(0.082)	(4.483)	(13.505)	(34.289)	(70.793)	(0.053)	(0.049)
Exposed to Policies	1.633***	0.211***	20.970***	69.110**	301.430***	37.583	1.633***	0.269***
	(0.166)	(0.072)	(7.995)	(31.327)	(52.327)	(88.740)	(0.205)	(0.068)
More Restrictive Medical School Policies × Exposed to Policies	1.271	-0.311**	-22.585*	-56.720	-210.000**	20.123	1.271	-0.263*
	(0.250)	(0.129)	(12.498)	(42.836)	(88.590)	(197.115)	(0.242)	(0.142)
Observations	8 657	5 608	5 608	5 608	5 608	5 608	8 657	5 608

Notes: All models include years fixed effects. Bootstrapped standard errors in parentheses, $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

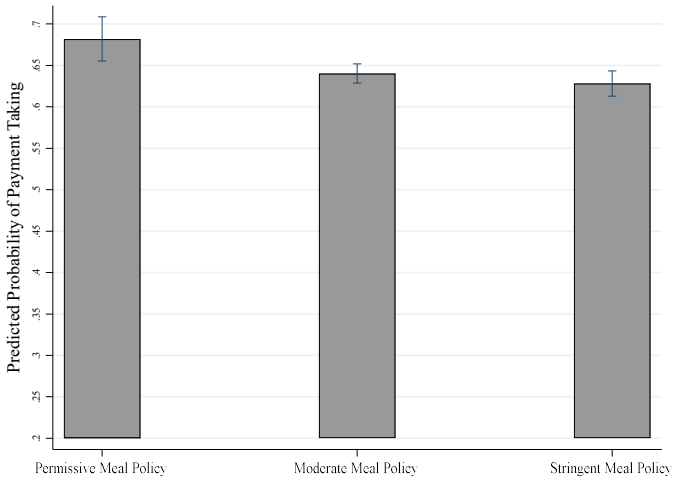
I, next, investigate the impact of medical school policies and being exposed to such policies in greater depth by allowing the impact of each to vary according to the level of the other (I interact them). In the set of regressions presented in table 3.3, a division of medical school policy index into highly restrictive and less restrictive hospital policies was conducted. The results show that being exposed to highly restrictive policies in medical school does not affect the likelihood of accepting payments or interacting with pharmaceutical sales representatives. However, being exposed to policy changes in medical school does affect the size of accepted payments and frequency of interactions with pharmaceutical sales representatives later in a physician's career.

Figure 3.1 indicates that food and beverage-related payments constitute for the majority (73 percent) of overall accepted payments. Next, I investigate the effect of medical school meal policies on acceptance of food-related payments later in a physician's career. The results in Table 3.4 mostly match those reported in table 3.2. Table 3.4 and figure 3.4 indicate that medical school meal policies are associated with lower likelihood of accepting food-related payments by family medicine doctors later in their careers. Thus, a physician who attended medical school with stringent meal policies is less likely to accept food-related payments from pharmaceutical company than a physician who attended medical school with permissive meal policies.

Table 3.4: Food and beverage-related payments

	Total Payments						Frequency of Payments	
	Logit	GLM	Quantile Regressions				Logit	GLM
	Payment > 0 (1)	Log Payment > 0 (2)	25th Percentile (3)	50th Percentile (4)	75th Percentile (5)	90th Percentile (6)	Payment > 0 (7)	Log Payment > 0 (8)
Medical School Meal Policy	0.897*** (0.030)	-0.037 (0.027)	-4.177 (2.919)	-25.665*** (7.583)	-24.132 (23.487)	-26.467 (40.566)	0.897*** (0.029)	-0.027 (0.026)
Exposed to Policies	1.710*** (0.130)	0.188*** (0.045)	15.783* (8.207)	45.929*** (15.656)	255.510*** (50.331)	24.120 (62.400)	1.710*** (0.127)	0.207*** (0.051)
Female physician	0.629*** (0.028)	-0.319*** (0.041)	-20.470*** (4.344)	-105.043*** (12.249)	-285.148*** (35.975)	-431.480*** (60.494)	0.629*** (0.030)	-0.372*** (0.036)
Years in practice	1.051*** (0.009)	0.055*** (0.007)	2.837*** (0.751)	16.829*** (2.184)	47.593*** (6.704)	53.283*** (12.250)	1.051*** (0.010)	0.064*** (0.007)
State adopted disclosure policies prior to Sunshine Act	0.274*** (0.029)	-0.261* (0.179)	-25.180*** (3.846)	-114.861*** (14.122)	-264.669*** (49.978)	-85.815 (325.517)	0.274*** (0.025)	-0.179 (0.129)
Size of Physician Practice (<=5, 6-25)	0.657*** (0.033)	-0.216*** (0.036)	-18.337*** (6.381)	-93.112*** (13.551)	-228.566*** (37.756)	-273.155*** (70.988)	0.657*** (0.039)	-0.132*** (0.041)
Observations	8 655	5 541	5 541	5 541	5 541	5 541	8 655	5 541

Notes: All models include years fixed effects. Bootstrapped standard errors in parentheses, $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$



Notes: Estimates are from equation 3.1 with all other variables fixed at their sample means.

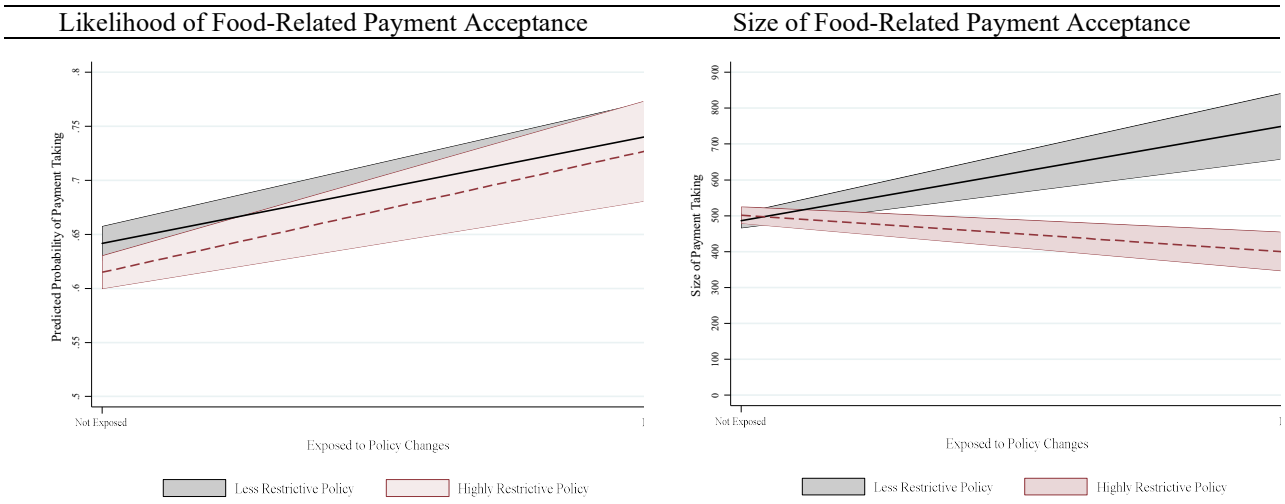
Figure 3.4: Likelihood of payment acceptance by meal policies

For the purposes of analyses in table 3.5, I divide medical school meal policies into stringent and non-stringent (permissive and moderate) meal policies. Table 3.5 and figure 3.5 show that being exposed to stringent meal policies while a medical student, has indistinguishable from zero effect on the likelihood of accepting promotional payments and interactions with pharmaceutical sales representatives. However, exposure to stringent meal policies at medical school is associated with lower average payment acceptance (column 2) and lower frequency of interactions (column 8). An exposure to stringent meal policies is also associated with lower size of accepted payments at the median (as well as at 25, 75 and 90th percentiles). Thus, the medical school policies do affect the behavior of family medicine doctors later in their careers. This result is in line with the King et al. (2013) findings and contradicts the McCormick et al. (2001) and Ferguson at al. (1999) studies.

Table 3.5: Exposure to medical school meal policies

	Total Payments						Frequency of Payments	
	Logit	GLM	Quantile Regressions				Logit	GLM
	Payment > 0 (1)	Log Payment > 0 (2)	25th Percentile (3)	50th Percentile (4)	75th Percentile (5)	90th Percentile (6)	Payment > 0 (7)	Log Payment > 0 (8)
Stringent Medical School Meal Policy	0.886** (0.045)	0.031 (0.035)	-1.153 (5.076)	-8.056 (15.504)	22.142 (38.964)	-6.480 (69.862)	0.886** (0.042)	0.062 (0.056)
Exposed to Policies	1.657*** (0.193)	0.442*** (0.069)	34.348*** (12.247)	182.366*** (74.106)	445.285*** (65.138)	287.913** (138.399)	1.657*** (0.179)	0.462*** (0.075)
Medical School Meal Policy × Exposed to Policies	1.052 (0.179)	-0.675*** (0.094)	-37.249*** (13.598)	-200.514*** (75.455)	-504.953*** (82.070)	-509.237*** (162.412)	1.052 (0.197)	-0.665*** (0.112)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8 655	5 541	5 541	5 541	5 541	5 541	8 655	5 541

Notes: All models include years fixed effects. Bootstrapped standard errors in parentheses, $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$



Notes: Estimates are from interaction term between exposure to policy change and hospital meal policy index, with all other variables described in equation 3.1 fixed at their sample means. Highly restrictive hospital policy index contains medical schools with stringent meal policies, while less restrictive hospital policy index contains those with permissive and moderate policies.

Figure 3.5: Food-related payment acceptance when exposed to meal policies

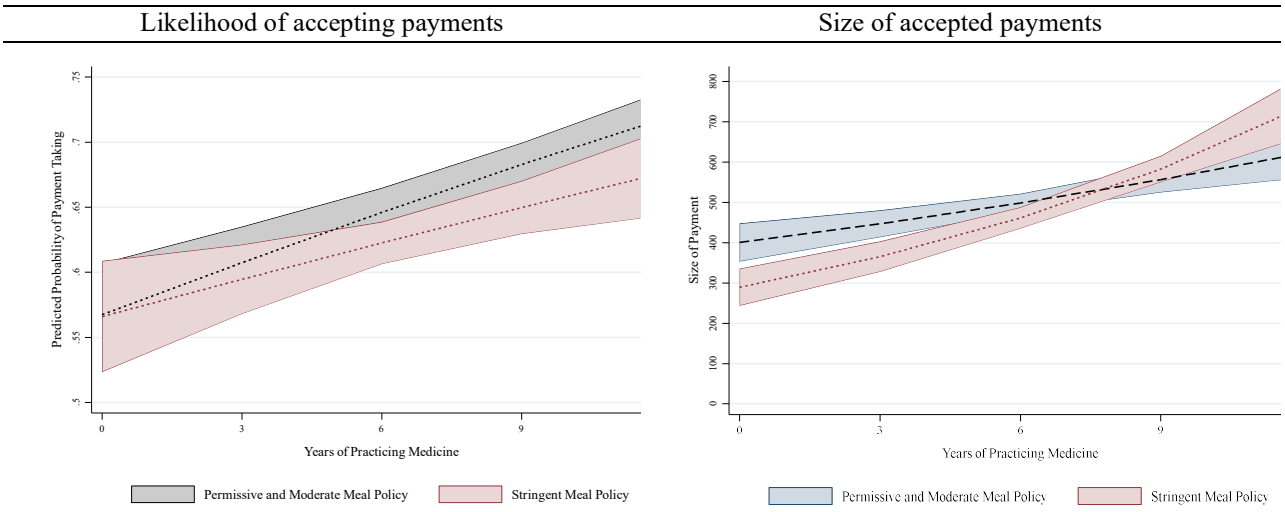
As was noted earlier in this chapter, there have been calls to change medical school policies and restrict interactions between medical students and pharmaceutical sales representatives. Restricting interactions, especially those related to provision of food and beverages from pharmaceutical sales representatives, may prove to be important in reducing acceptance of payments from pharmaceutical industry later in a physician's career.

Table 3.6: Medical school policies and years of practicing medicine

	Total Payments						Frequency of Payments	
	Logit	GLM	Quantile Regressions				Logit	GLM
	Payment >0 (1)	Log Payment >0 (2)	25th Percentile (3)	50th Percentile (4)	75th Percentile (5)	90th Percentile (6)	Payment >0 (7)	Log Payment >0 (8)
Stringent Medical School Meal Policy	0.994 (0.089)	-0.325*** (0.072)	-16.121* (9.434)	-86.380*** (20.098)	-247.806*** (64.459)	-205.652 (139.016)	0.994 (0.108)	-0.241*** (0.093)
Years of practicing medicine	1.060*** (0.012)	0.037*** (0.008)	1.959** (0.914)	11.463*** (2.843)	29.234*** (9.402)	47.968*** (14.796)	1.060*** (0.012)	0.049*** (0.009)
Medical School Meal Policy × Years of practicing medicine	0.983 (0.013)	0.041*** (0.009)	1.899 (1.445)	10.672** (4.348)	32.356*** (8.970)	19.415 (20.188)	0.983 (0.014)	0.033*** (0.012)
Observations	8 655	5 541	5 541	5 541	5 541	5 541	8 655	5 541

Notes: All models include years fixed effects. Bootstrapped standard errors in parentheses, $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table 3.6 investigates the combined effect of years of practicing medicine and medical school meal policies on the likelihood and size of accepted payments and interactions with pharmaceutical sales representatives. The results indicate that with each additional year of practicing medicine physicians are more likely to accept and interact with pharmaceutical sales representatives. Physicians also accept more in payments and interact more with pharmaceutical sales representative given that payments are positive (columns 2-6 and 8). As physicians practice medicine for longer period of time, enjoy patients' confidence in their work and assume leadership roles in their groups, they are more likely to be approached by pharmaceutical sales representatives and be offered larger promotional payments. Throughout years of practicing medicine, physicians may also build stronger connections with pharmaceutical sales representatives. The analysis indicates that medical school meal policies have no statistically significant effect on the likelihood of accepting food-related payments and interactions. However, stringent medical school meal policies are associated with decreased size of accepted payments and interactions with pharmaceutical sales representatives, everything else constant. Finally, table 3.6 and figure 3.6 show that the combined effect of medical school meal policies and years of practicing medicine has no statistically significant effect on the likelihood of accepting food and beverage related payments.



Notes: Estimates are from interaction term between variables years of practicing medicine and hospital meal policy index, with all other variables described in equation 3.1 fixed at their sample means.

Figure 3.6: Meal policies and years of practicing medicine

While food and beverage payments constitute for a sizeable portion of payments, pharmaceutical sales representatives also approach physicians offering other types of payments. Next, I examine the effect of medical school policies on size and likelihood of accepting different types of payments.

Table 3.7: Payments by types, logit[27]

	Speaker Fees	Consulting Fees	Travel & Lodging	Educational Payments
Medical School Policy Index	1.215 (0.175)	1.024 (0.089)	0.952 (0.087)	0.947* (0.027)
Exposed to policies	0.687 (0.378)	0.800 (0.269)	0.215*** (0.077)	1.490*** (0.165)
Female physician	0.844 (0.180)	0.488*** (0.081)	0.533*** (0.142)	0.563*** (0.029)
Years in practice	1.091** (0.047)	1.135*** (0.029)	1.135*** (0.042)	1.090*** (0.011)
State adopted disclosure policies prior to Sunshine Act	0.399 (0.227)	0.121*** (0.052)	1.049 (0.618)	0.378*** (0.067)
Size of Physician Practice (<=5, 6-25)	0.563*** (0.111)	0.846 (0.156)	0.355*** (0.076)	0.541*** (0.031)
Observations	8 655	8 655	8 655	8 655

Notes: All models include years fixed effects. Bootstrapped standard errors in parentheses, $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Results in table 3.7 imply that more restrictive medical school policies affect the likelihood of accepting educational payments later in a physician's career. Exposure to medical school policies is associated with lower likelihood of travel and lodging and higher likelihood of educational-related payment acceptance. Table 3.7 also reveals that female physicians adopt somewhat different behavior regarding acceptance of various types of promotional payments. Female physicians are less likely to accept in travel and lodging, consulting and educational payments, but tend to adopt similar behavior to that of their male colleagues with regards to speaker-related payments.

[27] Gift and entertainment-related payments were excluded from analysis in tables 3.7 and 3.8 because of low observations.

Table 3.8: Payments by types, GLM

	Speaker Fees	Consulting Fees	Travel & Lodging	Educational Payments
Medical School Policy Index	-0.481 (0.397)	0.381* (0.214)	0.023 (0.251)	0.022 (0.054)
Exposed to policies	-2.180 (1.708)	-0.636 (0.663)	1.344*** (0.495)	-0.550** (0.218)
Female physician	-0.171 (1.879)	0.478 (0.579)	-0.710* (0.381)	-0.328*** (0.099)
Years in practice	0.408** (0.187)	0.330*** (0.071)	0.200** (0.082)	-0.060 (0.043)
State adopted disclosure policies prior to Sunshine Act	-7.218*** (1.108)	-2.013*** (0.503)	0.231 (0.472)	-0.267 (0.300)
Size of Physician Practice (<=5, 6-25)	-1.101 (0.888)	-0.898* (0.487)	-0.188 (0.375)	-0.417** (0.168)
Observations	88	153	64	1 462

Notes: All models include years fixed effects. Bootstrapped standard errors in parentheses, $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Results in table 3.8 mainly indicate that medical school policies do not affect the size of accepted payments. Only consulting-related payments seem to have positive association with stringency of medical school policies (significant at 10 percent level). Such an outcome may be driven by the fact that most medical schools with more stringent meal and gift policies are relatively known ones. Graduates from such schools may end up being opinion leaders in their groups and medical community and be offered larger consulting-related payments. Unfortunately, this hypothesis will remain untested within the scopes of this study. My a priori expectation was that medical school policies would have a large effect on acceptance of all types of payments later in physician's career. Alas, no statistically significant effect was found between medical school policies and likelihood and size of most types of payments, especially for those that have contractual nature (such as speaker fees and consulting-related payments).

Overall, this study showed that adopting restrictive meal and gift policies at medical schools may help to reduce the propensity of some types of promotional payment acceptance later in a physicians' career.

3.5 Conclusion

Pharmaceutical industry influence can harm the social and moral character of physicians and affect their prescribing habits. Pharmaceutical companies recognize the potential for education as a marketing tool. An early exposure to pharmaceutical promotions may communicate a biased message, encouraging overuse of particular products (Austad, Avorn and Kesselheim, 2011) and building loyalty to pharmaceutical company which can have a lasting effect. Realizing the effect of industry relationships on future prescribing habits of physicians, some medical schools implemented policies forbidding interactions between students and faculty with pharmaceutical sales representatives. To this day, little empirical research has examined the efficacy of different types of conflict of interest policies. This work extends previous research by studying the effect of medical school policies on promotional payment acceptance later in physician's career.

The chapter analyzed the relationship between medical school policies, exposure to such policies, gender, tenure, size of physician group and acceptance of promotional payments. It showed that female physicians are less likely to accept payments and interact with pharmaceutical sales representatives compared to their male counterparts. Female physicians tend to also accept less in promotional payments than their male colleagues. Additionally, the study showed that physicians interact more with pharmaceutical representatives and accept more

in promotional payments with each additional year of practicing medicine. Perhaps, as physicians practice medicine for longer periods of time, become leaders in their groups and establish relationships with pharmaceutical industry, they are more likely to be approached by pharmaceutical sales representatives and be offered promotional payments. The study also argued that physicians practicing in small groups are more likely to be approached and accept more in promotional payments than their colleagues working in bigger family medicine practices.

More importantly, the chapter studied the relationship between medical school policies and propensity of promotional payment acceptance later in a physician's career. To this day little empirical work exists to guide the policy choices for strategies that manage physician-industry interactions. This work suggests that some medical school policies affect the likelihood and the size of accepted promotional payment and interactions with pharmaceutical representatives. The effect is the strongest for medical school meal policies on the reduction of accepted food and beverage-related payments from the pharmaceutical industry later in a physician's career. While industry relationships may be an unavoidable aspect in the delivery of healthcare, there are measures that can be undertaken to minimize the industry's influence on physicians' interactions with pharmaceutical industry and thus on their prescribing habits. Adopting stringent medical school policies and especially stringent meal policies may prove to have a considerable effect on shaping trainees' perceptions and having a long-lasting effect on physicians' behavior.

BIBLIOGRAPHY

Acemoglu, D., Johnson, S. & Robinson, J. (2006) Institutions as a Fundamental Cause of Long-Run Growth. In Handbook of Economic Growth, Volume iA, edited by Philippe Aghion and Steven N. Durlauf: 385-394.

Achim, M. (2016). Cultural Dimension of Corruption: A Cross-Country Survey. International Advances in Economic Research, 22: 333–345.

Akande, T. & Aderibigbe, S. (2007). Influence of drug promotion on prescribing habits of doctors in a teaching hospital.Arican Sournal of Medicine and Medical Sciences, 36(3): 207-211.

Alatas,V., Cameron, L., Chaudhuri, A., Erkal, N. & Gangadharan, L. (2009). Gender, Culture, and Corruption: Insights from an Experimental Analysis. Southern Economic Journal, 75(3): 663-680.

Al-Areefi, M., Hassali, M. & Mohamed Ibrahim, M. (2013). The role of pharmaceutical marketing and other factors in prescribing decisions: the Yemeni experience. Research in Social & Administrative Pharmacy, 9(6): 981–988.

Alssageer, M. & Kowalski, S. (2012). A survey of pharmaceutical company representative interactions with doctors in Libya. Libyan Journal of Medicine, 7(1).

American Immigration Council. (2018). Foreign-Trained Doctors are Critical to Serving Many U.S. Communities.

American Medical Association. Resident Physicians Section. (1993). Guidelines for interactions with pharmaceutical companies. Journal of American Medical Association, 270: 1250.

American Medical Student Association. House of Delegates. (2003). AMSA policy on pharmaceutical promotions.

Auruskeviciene, V., Butkeviciene, J. & Salciuviene, L. (2015). Revisiting the Role of Traditional, Electronic and Mobile-Based Communication Channels in the Pharmaceutical Industry of Lithuania. Inzinerine Ekonomika-Engineering Economics, 26(5): 541–550.

Austad, K. Avorn, J. & Kesselheim, A. (2011). Medical Students' Exposure to and Attitudes about the Pharmaceutical Industry: A Systematic Review. PLOS Medicine, 8(5).

Banerjee, R. (2016). On the interpretation of bribery in a laboratory corruption game: moral frames and social norms. Experimental Economics, 19: 240–267.

Bansal, R., Backer, R. & Ranade, V. (2018). What's behind the pharmaceutical sector's M&A push. McKinsey and Company. https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/whats-behind-the-pharmaceutical-sectors-m-and-a-push .

Barr, A. & Serra, D. (2010). Corruption and culture: An experimental analysis. Journal of Public Economics, 94 (11-12): 862-869.

Basu, A. & Rathouz, P. (2005). Estimating marginal and incremental effects on health outcomes using flexible link and variance function models. Biostatistics, 6(1):93-109.

Bellin, M.; McCarthy, S; Drevlow, L.; Pierach, C. (2004). Medical Students' Exposure to Pharmaceutical Industry Marketing: A Survey at One U.S. Medical School. Academic Medicine, 79(11): 1041-1045.

Belotti, F., Partha, D., Manning, W. & Norton, E. (2015). twopm: Two-part models. The Stata Journal, 15(1): 3–20.

Berenson, A., Harris, G. & Meier, B. (2004). Despite Warnings, Drug Giant Took Long Path to Vioxx Recall. The New York Times. https://www.nytimes.com/2004/11/14/business/despite-warnings-drug-giant-took-long-path-to-vioxx-recall.html

Bhat, V. (2005). Patent term extension strategies in the pharmaceutical industry. Pharmaceuticals Policy and Law, 6: 109–122.

Bicchieri, C. & Rovelli, C. (1995). Evolution and Revolution: The Dynamics of Corruption. Rationality and Society, 7(2): 201-224.

Blundo, G. (2008). Hidden Acts, Open Talks. How Anthropology can "Observe" and Describe Corruption. Ed. M. Nuijten and G. Anders. Abingdon: Ashgate Publishing Group.

Bourdieu, P. (1997). Marginalia - Some Additional Notes of the Gift. In The Logic of the Gift, Ed. A. D. Schrift. New York: Routlege.

Box, G. & Cox, D. (1964). An analysis of transformations. Journal of the Royal Statistical Society, Series B, 26: 211– 252.

Breen, M., Gillanders, R., Mcnulty, G. & Suzuki, A. (2017). Gender and Corruption in Business, The Journal of Development Studies, 53(9): 1486-1501.

Brotzman, G. & Mark D. (1993). The effect on resident attitudes of regulatory policies regarding pharmaceutical representative activities. Journal of General Internal Medicine, 8:130–134.

Burashnikova, I., Ziganshin, A., & Ziganshina, L. (2008). Attitudes to pharmaceutical promotion techniques among healthcare professionals in the Republic of Tatarstan, Russia. International Journal of Risk & Safety in Medicine, 20(1/2): 57-71.

Cameron, L., Chaudhuri, A., Erkal, N. & Gangadharan, L. (2009). Propensities to engage in and punish corrupt behavior: Experimental evidence from Australia, India, Indonesia and Singapore. Journal of Public Economics, 93(7–9): 843-851.

Cameron, A. & Trivedi, P. (2013). Regression Analysis of Count Data. 2nd ed. Cambridge: Cambridge University Press.

Campbell, E., Gruen, R., Mountford, J, Miller, L., Cleary, P. & Blumenthal, D. (2007). A national survey of physician-industry relationships. New England Journal of Medicine, 356(17): 1742–1750.

Campbell, E., Rao, S., DesRoches, C. et al. (2010). Physician professionalism and changes in physician-industry relationships from 2004 to 2009. Archives of Internal Medicine, 170(20): 1820-1826.

Cascardo, D. (2009) Compliance Issues for Small and Medium-size Physician Practices. The Journal of Medical Practice Management, 25(1): 25-28.

Caves, R., Whinston, M. & Hurwitz, M. (1991) Patent Expiration, Entry, and Competition in the U.S. Pharmaceutical Industry. Brookings Papers on Economic Activity: Microeconomics. Washington, DC: Brookings Institution.

Caudill, T., Johnson, M., Rich, E. & McKinney, W. (1996). Physicians, pharmaceutical sales representatives, and the cost of prescribing. Archives of Family Medicine, 5: 201–206.

Caudill, T., Lurie, N. & Rich, E. (1992). The influence of pharmaceutical industry advertising on physician prescribing. Journal of Drug Issues, 22(2): 331-338.

Cawley, J. & Meyerhoefer, C. (2012). The medical care costs of obesity: an instrumental variables approach. Journal of Health Economics. 31: 219–230.

Centers for Medicare and Medicaid Services (2021). User Guide for Covered Recipients. Open Payments. Creating Public Transparency Into Industry-Physician Financial Relationships.

Chandon, P. (2004). Innovative marketing strategies after patent expiry: The case of GSK's antibiotic Clamoxyl in France. International Journal of Medical Marketing, 4(1): 65–73.

Ching, A. & Ishihara, M. (2012) Measuring the Informative and Persuasive Roles of Detailing on Prescribing Decisions. Management Science, 58(7): 1374-1387.

Chiu, C-y., Gelfand, M., Yamagishi, T., Shteynberg, G. & Wan, C. (2010). Intersubjective culture: The role of intersubjective perceptions in cross-cultural research. Perspectives on Psychological Science, 5: 482-493.

Chressanthis, G., Dahan, N. & Fandl, K. (2015). The Effects of State Pharmacy Drug Product Selection Laws on Statin Patient Generic-to-Brand Drug Switch-Backs. The American Economist; 60(1): 26-51.

Cockburn, I. (2004). The Changing Structure Of The Pharmaceutical Industry. Health Affairs, 23(1).

Collier, R. (2009). Drug development cost estimates hard to swallow. CMAJ, 180(3): 279-280.

Congressional Research Service (2020). Drug Pricing and Pharmaceutical Patenting Practices. CRS Report. R46221. https://crsreports.congress.gov/ .

Davies, G., Whelan, S., Foey, A. & Walsh, M.(2009). Gifts and Gifting. International Journal of Management Reviews, 12: 413–434.

Davies, J. & Ruhe, J. (2003). Perceptions of Country Corruption: Antecedents and Outcomes. Journal of Business Ethics, 43(4): 275-288.

De Laat, E., Windmeijer, F., & Douven, R. (2002). How does pharmaceutical marketing influence doctors' prescription behaviour? The Hague: CPB Netherlands' Bureau for Economic Policy Analysis.

Deb, P. & Norton, E. (2018). Modeling Health Care Expenditures and Use. Annual review of Public Health, 39(1): 489-505.

Deb, P., Norton, E. & Manning, W. (2017). Health Econometrics Using Stata. College Station, TX: Stata Press.

DeBacker, J., Bradley,T. & Heim, A. (2015). Importing corruption culture from overseas: Evidence from corporate tax evasion in the United States. Journal of Financial Economics, 117(1): 122-138.

DeJong, C., Aguilar, T., Tseng, C., Lin, G., Boscardin, W. & Dudley, R. (2016). Pharmaceutical Industry-Sponsored Meals and Physician Prescribing Patterns for Medicare Beneficiaries. JAMA Internal Medicine, 176(8): 1114-1122.

Della Porta, D. & Vannucci, A. (2004). Governance Mechanisms of Corrupt Transactions. in The New Institutional Economics of corruption, Ed. J. G. Lambsdorff, M. Taube and M. Schramm. New York: Routlege.

Department of Health and Human Services (2013). Federal Register. Rules and Regulations 78:27.

Diaz, R. (2011). Regulators, Watchdogs and Websites: Disclosure of Financial Conflicts of Interest. ABA Health Law Section 7(7).

Djankov, S., La Porta, R., López-De-Silanes, F. & Shleifer, A. (2002). The regulation of entry. Quarterly Journal of Economics, 117: 1 – 37.

Dollar, D., Fisman, R. & Gatti, R. (2001). Are women really the "fairer" sex? Corruption and women in government. Journal of Economic Behavior & Organization, 46(4): 423-429.

Eagly, A. & Crowley, M. (1986). Gender and Helping Behavior: A Meta-Analytic Review of the Social Psychological Literature. Psychological Bulletin, 100: 283-306.

Eckel, C. & Grossman, P. (1998). Are Women Less Selfish than Men? Evidence from Dictator Experiments. Economic Journal, 108: 726-735.

Engelberg, J., Parsons, C. & Tefft, N. (2014) Financial Conflicts of Interest in Medicine. Available at
SSRN: https://ssrn.com/abstract=2297094 or http://dx.doi.org/10.2139/ssrn.2297094.

Epstein, A., Busch, S., Busch, A, Asch, D. & Barry, C. (2013). Does Exposure to Conflict of Interest Policies in Psychiatry Residency Affect Antidepressant Prescribing? Medical Care, 51(2): 199-203.

Federal Trade Commission (2010). Pay-for-Delay: How Drug Company Pay-Offs Cost Consumers Billions. https://www.ftc.gov/reports/pay-delay-how-drug-company-pay-offs-cost-consumers-billions-federal-trade-commission-staff .

Fehr, E. & Fischbacher, U. (2004) Third-Party Punishment and Social Norms. Evolution and Human Behavior, 25 (2): 63–87.

Feldman, R. (2018). May your drug price be evergreen. Journal of Law and the Biosciences, 5(3): 590–647.

Feldman, R. & Frondorf, E. (2017). Drug Wars: How Big Pharma Raises Prices and Keeps Generics off the Market (p. iii). Cambridge University Press.

Ferguson, R., Rhim, E., Belizaire, W., et al. (1999) Encounters with pharmaceutical sales representatives among practicing internists. American Journal of Medicine, 107:149-152.

Fickweiler, F., Fickweiler, W. & Urbach, E. (2017). Interactions between physicians and the pharmaceutical industry generally and sales representatives specifically and their association with physicians' attitudes and prescribing habits: a systematic review. BMJ Open, 7(9), e016408.

Fischer, R. (2012). Intersubjective culture: Indeed intersubjective or yet another form of subjective assessment? [Special issue: Personality and Culture] Swiss Journal of Psychology, 71: 13-20.

Fischer, R., Ferreira, M., Milfont, T. & Pilati, R. (2014). Culture of Corruption? The Effects of Priming Corruption Images in a High Corruption Context. Journal of Cross-Cultural Psychology, 45(10): 1594-1605.

Fischer, M., Keough, M., Baril, J. et al. (2009) Prescribers and Pharmaceutical Representatives: Why Are We Still Meeting? Journal of General Internal Medicine, 24: 795–801.

Fisman, R. & Miguel, E. (2007). Corruption, norms, and legal enforcement: evidence from diplomatic parking tickets. Journal of Political Economy, 115 (6): 1020-1048.

Fitz, M., Homan, D., Reddy, S., et al. (2007). The Hidden Curriculum: Medical Students' Changing Opinions toward the Pharmaceutical Industry. Academic Medicine, 82 (10): S1-S3.

Folland, S., Goodman, A. & Stano, A.(2010). The Economics of Helath and Healthcare. Routledge.

George Washington University (2009). Impacts of Pharmaceutical Marketing on Healthcare Services in the District of Columbia. The George Washington University School of Public Health and Health Services for the District of Columbia Department of Health.

Glover, S., Bumpus, M., Logan, J. and Ciesla, J. (1997). Reexamining the Influence of Individual Values on Ethical Decision-Making. Journal of Business Ethics, 16: 1319-1329.

Goertzel, T. (1983). The Gender Gap: Sex, Family, Income, and Political Opinions in the Early 1980s. Journal of Political and Military Sociology, 11:209-222.

Graham, D., Campen, D., Hui, R. et al. (2005). Risk of acute myocardial infarction and sudden cardiac death in patients treated with cyclo-oxygenase 2 selective and non-selective non-steroidal anti-inflammatory drugs: Nested case-control study. The Lancet, 365: 475-481.

Grande, D., Frosch, D., Perkins, A. & Kahn B. (2009). Effect of exposure to small pharmaceutical promotional items on treatment preferences. Archives of Internal Medicine, 169(9): 887-893.

Greene, W. (2012). Econometric Analysis. Seventh Edition. Pearson Education Limited;

Gubby, H. (2019). Is the Patent System a Barrier to Inclusive Prosperity? The Biomedical Perspective. Global Policy, 11(1): 46-55.

Guiso, L., Sapienza, P. & Zingales, L. (2006). Does culture affect economic outcomes? Journal of Economic Perspectives, 20: 23-49.

Halkos, G. & Tzeremes, N. (2011). Investigating the cultural patterns of corruption: A nonparametric analysis, MPRA Munich Personal RePEc Archive.

Halter, M., Coutindo de Arruda, M. & Halter, R. (2009). Transparency to Reduce Corruption? Dropping Hints for Private Organizations in Brazil. Journal of Business Ethics, 84(3): 373-385.

Heckman, J. (1979). Sample selection bias as a specification error. Econometrica, 47: 153–161.

Handa, M., Vohra, A. & Srivastava, V. (2013). Perception of physicians towards pharmaceutical promotion in India. Journal of Medical Marketing, 13(2): 82-92.

Harrison, C. (2004). The Politics of the International Pricing of Prescription Drugs. Praeger.

Heckman, J. (1979). Sample selection bias as a specification error. Econometrica, 47: 153–161.

Hipp, L. & Lawler, E. (2010). Corruption as Social Exchange. Paper presented at the105th Annual Meeting of the American Sociological Association, Atlanta, USA, August 2010.

Hodges, B. (1995). Interactions with the pharmaceutical industry: experiences and attitudes of psychiatry residents, interns and clerks. The Canadian Medical Association Journal, 153: 553–559.

Huang, F., Weiss, D., Fenimore, P., et al. (2005). The association of pharmaceutical company promotional spending with resident physician prescribing behavior. Academic Psychiatry, 29(5): 500-501.

Iizuka, T. (2004). What Explains the Use of Direct-to-Consumer Advertising of Prescription Drugs? Journal of Industrial Economics, 52(3): 349–79.

Jancsics, D. (2014). Interdisciplinary Perspectives on Corruption. Sociology Compass, 8(4): 358–372.

Jimenez, J. (2012) The CEO of Novartis on growing after a patent cliff. Harvard Business Review, 90: 39–42.

Jones, A. (1989). A double-hurdle model of cigarette consumption. Journal of Applied Econometrics, 4: 23–39.

Jones, R. & Ornstein, C. (2016). Matching Industry Payments to Medicare Prescribing Patterns: An Analysis. Propublica: 1–10.

Kakkar, K. (2015). Patent cliff mitigation strategies: giving new life to blockbusters. Expert Opinion on Therapeutic Patents, 25(12): 1353-1359.

Katz, D., Caplan, A. & Merz, J. (2003) All Gifts Large and Small. The American Journal of Bioethics, 3(3): 39-46.

Keim, S., Mays, M. & Grant, D. (2004). Interactions between emergency medicine programs and the pharmaceutical industry. Academic Emergency Medicine, 11:19–26.

Keim, S., Sanders, A., Witzke, D., Dyne, P. & Fulginiti, J. (1993). Beliefs and practices of emergency medicine faculty and residents regarding professional interactions with the biomedical industry. Annals of Emergency Medicine, 10:1576-1581.

Kerak, E., Louhoudi, H. & Ouardouz, M. (2014). Assessment of the quality of the services provided by pharmaceutical representatives: Case of Moroccan delegates from the region of Salé. International Journal of Innovation and Applied Studies, 8(2): 451–467.

King, M., Essick, C., Bearman, P. & Ross, J. (2013). Medical School Gift Restriction Policies and Physician Prescribing of Newly Marketed Psychotropic Medications: A Difference-in-Difference Analysis. British Medical Journal.

King, M. & Bearman, P. (2017). Gifts and influence: Conflict of interest policies and prescribing of psychotropic medications in the United States. *Social Science and Medicine*, 172: 153.

Kluckhohn, C. (1951). The study of culture. In: D. Lerner & H. D. Lasswell (Eds.), The policy sciences. Stanford: Stanford University Press.

Köbis, N., Iragorri-Carter, D., Starke, C. (2018). A Social Psychological View on the Social Norms of Corruption. In: Kubbe I., Engelbert A. (eds) Corruption and Norms. Political Corruption and Governance. Palgrave Macmillan, Cham.

Kuper, A. (1999). Culture—The anthropologists' account. London, England: Harvard University Press.

Lacy, S. & Martin, H. (2004). Competition, Circulation And Advertising. Newspaper Research Journal, 25(1): 18-39.

Laffont, J. & Tirole, J. (1991). The politics of government decision-making: a theory of regulatory capture. The Quarterly Journal of Economics, 106: 1089-1127.

Lê Cook, B., McGuire, T., Lock, K. & Zaslavsky, A. (2010). Comparing methods of racial and ethnic disparities measurement across different settings of mental health care. Health Services Research, 45: 825–847.

Lê Cook, B. & Manning, W. (2013). Thinking beyond the mean: a practical guide for using quantile regression methods for health services research. Shanghai Archives of Psychiatry, 25(1): 55-59.

Lederman, D., Loayza, N. & Soares, R. (2005). Accountability and Corruption: Political. Economics and Politics, 17(1): 1-35.

Leffler, K. (1981). Persuasion or Information? The Economics of Prescription Drug Advertising. The Journal of Law & Economics, 24(1): 45-74.

Lexchin, J. (1997). What information do physicians receive from pharmaceutical representatives? Canadian Family Physician, 43: 941-945.

Lichstein, P., Turner, R. & O'Brien, K. (1992). Impact of pharmaceutical company representatives on internal medicine residency programs. A survey of residency program directors. Archives of Internal Medicine, 152: 1009–1013.

Lurie, N., Rich, E., Simpson, D., et al. (1990). Pharmaceutical representatives in academic medical centers: interactions with faculty and housestaff. Journal of General Internal Medicine, 5: 240–243.

Madhavan, S., Amonkar, M., Elliott, D., Burke, K. & Gore, P. (1997). The gift relationship between pharmaceutical companies and physicians: an exploratory survey of physicians. Journal of Clinical Pharmacy and Therapeutics, 22: 207–215.

Mahan, D. (2002). Profiting from Pain: Where Prescription Drug Dollars Go. Publication No. 02-105. Washington, DC: Families USA; Available at: www.familiesusa.org .

Makurvet, F. (2021). Biologics vs. small molecules: Drug costs and patient access. Medicine in Drug Discovery, 9: 757-758.

McCormick, B., Tomlinson, G., Brill-Edwards, P. & Detsky, A. (2001). Effect of restricting contact between pharmaceutical company representatives and internal medicine residents on posttraining attitudes and behavior. Journal of American Medical Association, 286: 1994–1999.

McGettigan, P., Golden, J., Fryer, J., Chan, R. & Feely, J. (2000). Prescribers prefer people: the sources of information used by doctors for prescribing suggest that the medium is more important than the message. British Journal Clinical Pharmacology, 51: 184–189.

Mihaylova, B., Briggs, A., O'Hagan, A. & Thompson, S. (2011). Review of statistical methods for analysing healthcare resources and costs. Health Economics, 20: 897–916.

Mintzes, B., Lexchin, J., Sutherland, J., Beaulieu, M., Wilkes, M., Durrieu, G. & Reynolds, E. (2013). Pharmaceutical sales representatives and patient safety: a comparative prospective study of information quality in Canada, France, and the United States. Journal of General Internal Medicine, 28 (10): 1368-1375.

Mittra, J. & Tait, J. (2012). Analysing stratified medicine business models and value systems: innovation–regulation interactions. New Biotechnology, 29: 709–719.

Mooney, C. & Duval, R. (1993). Bootstrapping: A nonparametric approach to statistical inference. Newbury Park CA: Sage.

Morris, J. & Polese, A. (2014). Informal Health and Education Sector Payments in Russian and Ukrainian Cities: Structuring Welfare from Below. European Urban and Regional Studies, 23(3): 481-496.

Morrison, A. (2000). An analysis of anti-kickback and self-referral law in modern health care. Journal of Legal Medicine, 21: 351–394.

Norton, E. & Dowd, B. (2017). Log odds and the interpretation of logit models. Health Services Research, 53(2): 859-878.

Ones, D. & Viswesvaran, C. (1998). The Effects of Individual Difference Factors on Overt Integrity Tests: Results across Four Large-Scale Job Applicant Data Sets. Journal of Applied Psychology, 83: 35-42.

Othman, N., Vitry, A., Roughead, E., et al. (2010). Medicines information provided by pharmaceutical representatives: a comparative study in Australia and Malaysia. BMC Public Health, 10: 743.

Pammolli, F., Magazzini, L. & Riccaboni, M. (2011). The productivity crisis in pharmaceutical R&D. Nature Reviews Drug Discovery, 10: 428–438.

Park, R. (1966). Estimation with heteroscedastic error terms. Econometrica, 34: 888.

Parsons, T. & Shils, E. (1990). Values and social systems. In: J. Alexander & S. Seidman (Eds.), Culture and society, contemporary debates. Cambridge University Press: New York.

Paul, S., Mytelka, D., Dunwiddie, C., Persinger, C., Munos, B., Lindborg, S. & Schacht, A. (2010). How to improve R&D productivity: the pharmaceutical industry's grand challenge. Nature Reviews Drug Discovery, 9: 203–214.

Pena López, J. & Sánchez Santos, J. (2013). Does Corruption Have Social Roots? The Role of Culture and Social Capital. Journal of Business Ethics, 122(4): 697-708.

Perlis, R. & Perlis, C. (2016). Physician Payments from Industry Are Associated with Greater Medicare Part D Prescribing Costs. PLoS One, 11(5): e0155474.

QuintilesIMS Institute. (2017). Orphan Drugs in the United States. Providing Context for Use and Cost. https://rarediseases.org/wp-content/uploads/2017/10/Orphan-Drugs-in-the-United-States-Report-Web.pdf .

Reeder, M., Dougherty, J. & White, L. (1993). Pharmaceutical representatives and emergency medicine residents: a national survey. The Annals of Emergency Medicine, 22: 1593–1596.

Richer, A. (2019). Pharmaceutical exec guilty of bribing doctors to push opioid. APNews, https://apnews.com/82f638d6dfcf4193ad28ddf0e65897e1 .

Ricker-Gilbert, J., Jayne, T. & Chirwa, E. (2011). Subsidies and Crowding Out: A Double Hurdle Model of Fertilizer Demand in Malawi. American Journal of Agricultural Economics, 93(1): 26–42.

Sandberg, W., Carlos, R., Sandberg, E. & Roizen, M. (1997). The effect of educational gifts from pharmaceutical firms on medical students' recall of company names or products. Academic Medicine, 72(10): 916-918.

Sarikaya, O., Civaner, M. & Vatansever, K. (2009). Exposure of medical students to pharmaceutical marketing in primary care settings: frequent and influential. Advances in Health Sciences Education 14, 713.

Schwartz, L. & Woloshin, S. (2019). Medical Marketing in the United States, 1997-2016. Journal of American Medical Association, 321(1):80–96.

Scott Morton, F. (2000). Barriers to entry, brand advertising, and generic entry in the US pharmaceutical industry. International Journal of Industrial Organization, 18(7): 1085-1104.

Sen, A. (1997). Economics, business principles and moral sentiments. Business Ethics Quarterly, 7(3): 5-15.

Serra, D. (2006). Empirical determinants of corruption: A sensitivity analysis. Public Choice, 126(1): 225–256.

Sharma, M., Vadhariya, A., Johnson, M., Marcum, Z. & Hilmes, H. (2018). Association between industry payments and prescribing costly medications: an observational study using open payments and medicare part D data. BMC Health Services Research; 18(1): 236.

Sigworth, S., Nettleman, M. & Cohen, G. (2001). Pharmaceutical branding of resident physicians. Journal of American Medical Association, 286: 1024–1025.

Sloan, F. & Hsieh, C. (2012). Health Economics. The MIT.

Smerdon, D., Oerman, T. & Gneezy, U. (2020). 'Everybody's doing it': on the persistence of bad social norms. Experimental Economics, 23: 392–420.

Song, C. & Han, J. (2016) Patent cliff and strategic switch: exploring strategic design possibilities in the pharmaceutical industry. SpringlerPlus; 5(692).

Spurling, G., Mansfield, P., Montgomery, B., et al. (2010) Information from pharmaceutical companies and the quality, quantity, and cost of physicians' prescribing: a systematic review. PLoS Medicine, 7: e1000352.

Steinman, M., Shlipak, M. & S. McPhee. (2001). Of principles and pens: attitudes and practices of medicine housestaff toward pharmaceutical industry promotions. The American Journal of Medicine, 110(7): 551-557.

Sterne, J., White, I., Carlin, J., Spratt, M., et al. (2009). Multiple imputation for missing data in epidemiological and clinical research: potential and pitfalls. British Medical Journal, 338: b2393.

Stigler, G. (1971) The theory of economic regulation. Bell Journal of Economics, 2: 3-21.

Sung, H. (2003). Fairer Sex or Fairer System? Gender and Corruption Revisited. Social Forces, 82(2): 703–723.

Swamy, A., Knack, S., Lee, Y. & Azfar, O. (2001). Gender and Corruption. Journal of Development Economics, 64(1): 25-55.

Taylor, D. (2015). The Pharmaceutical Industry and the Future of Drug Development, in Pharmaceuticals in the Environment: 1-33.

Taylor, S., Huecker, J., Gordon, M., Vollman, D. & Apte, R. (2016). Physician-Industry Interactions and Anti-Vascular Endothelial Growth Factor Use Among US Ophthalmologists. JAMA Ophthalmology, 134(8): 897–903.

Tong W. (2014). Analysis of corruption from sociocultural perspectives, International Journal of Business and Social Science, 5(11(1)): 9–19.

Treisman, D. (2000). The causes of corruption: A cross-national study. Journal of Public Economics, 76(3): 399–457.

Tribble, S. & Lupkin, S. (2017). Drugmakers Manipulate Orphan Drug Rules to Create Prized Monopolies. Keiser Health News, https://khn.org/news/drugmakers-manipulate-orphan-drug-rules-to-create-prized-monopolies/.

Vainiomäki, M., Helve, O. & Vuorenkoski, L. (2004). A national survey on the effect of pharmaceutical promotion on medical students. Medical Teacher, 26(7): 630-634.

Vuorenkoski, L., Valta, M. & Helve, O. (2008). Effect of legislative changes in drug promotion on medical students: Questionnaire survey. Medical education, 42: 1172-1177.

Wall, L. & Brown, D. (2007). The high cost of free lunch. Obstetrics & Gynecology, 110: 169–173.

Wazana, A. (2000). Physicians and the pharmaceutical industry: is a gift ever just a gift? Journal of American Medical Association, 283: 373–380.

Weber, T. & Ornstein, C. (2010). Med Schools Flunk at Keeping Faculty Off Pharma Speaking Circuit. Dollars for Doctors, Propublica.

Wedderburn, R. (1974). Quasi-likelihood functions, generalized linear models, and the Gauss–Newton method. Biometrika, 61: 439–447.

Weiss, J. (2010). Medical Marketing in the United States : A Prescription for Reform. The George Washington Law Review, 79(1): 260–292.

Williams, S. (2003). Food for thought: why physicians should reconsider gifts from pharmaceutical companies. Journal of Current Surgery, 60: 152–153.

Windmeijer, F., De Laat, E., Douven, R. & Mot, E. (2006). Pharmaceutical promotion and GP prescription behaviour. Health Economics, 15(1): 5-18.

Wooldridge, J. (2010). Econometric Analysis of Cross Section and Panel Data. 2nd ed. Cambridge, MA: MIT Press.

World Health Organization (1998). WHO Ethical Criteria for Medicinal Drug Promotion. World Health Organization, Geneva.

Yeh, J., Franklin, J., Avorn, J., Landon, J. & Kesselheim, A. (2016). Association of Industry Payments to Physicians With the Prescribing of Brand-name Statins in Massachusetts. JAMA Intern Medicine, 176(6): 763–768.

Zhang, X., Lin, D., Pforsich, H. & V. Lin. (2020). Physician workforce in the United States of America: forecasting nationwide shortages. Human Resources for Health 18:8.

Zipkin, D. & Steinman, M. (2005). Interactions between pharmaceutical representatives and doctors in training: A thematic review. Journal of General Internal Medicine, 20: 777-786.

Sources:

American Hospital Association (2018). Hospital Statistics, Chicago.

Biosimilar Development, Review, and Approval. U.S. Food and Drug Administration. https://www.fda.gov/drugs/biosimilars/biosimilar-development-review-and-approval#process.

Centers for Medicare and Medicaid Services. Law and Policy. https://www.cms.gov/OpenPayments/Law-and-Policy.

Centers for Medicare and Medicaid Services. Nature of Payment. https://www.cms.gov/OpenPayments/Natures-of-Payment.

Doximity, https://www.doximity.com/ .

Food and Drug Administration. Department of Health and Human Services . CFR - Code of Federal Regulations Title 21. Food and drugs. Chapter 1. Subchapter D-Drugs for Human Use. Part 316 Orphan Drugs. https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfcfr/CFRSearch.cfm?CFRPart=316&showFR=1.

Food and Drug Administration. Orange book. https://www.accessdata.fda.gov/scripts/cder/ob/index.cfm.

Healthgrades, https://www.healthgrades.com/ .

Institute on Medicine as a Profession. Conflicts of Interest. http://imapny.org/conflicts-of-interest/advanced-coi-policy-search/ .

Md.com, https://www.md.com/.

NIS Description of Data Elements, https://www.hcup us.ahrq.gov/db/vars/hosp_bedsize/nisnote.jsp .

Open Payments. https://www.cms.gov/openpayments/index.html.

Transparency International. What is Corruption. https://www.transparency.org/en/what-is-corruption.

United States Patent and Trademark Office. https://www.uspto.gov/ .

Worldwide Governance Indicators (WGI). World Bank. https://globaledge.msu.edu/global-resources/resource/470.

World Bank.TCdata360. Control of Corruption. https://tcdata360.worldbank.org/indicators/hc153e067?country=BRA&indicator=364&viz=line_chart&years=1996,2020 .

APPENDIX A: EXCLUDING SOME COUNTRIES

Table A-1: Size and frequency of payments

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment>0 (2)	Interaction >0 (3)	Log Interaction> 0 (4)
Control of Corruption	0.681*** (0.037)	-0.246*** (0.090)	0.681*** (0.037)	-0.105** (0.050)
Hospital Policy	0.764*** (0.016)	0.139*** (0.037)	0.764*** (0.016)	-0.005 (0.021)
Gender (female=1)	0.673*** (0.027)	-0.198*** (0.062)	0.673*** (0.027)	-0.269*** (0.039)
Years of practicing medicine in the U.S.	1.065*** (0.003)	0.072*** (0.005)	1.065*** (0.003)	0.059*** (0.003)
State Disclosure Policies	0.317*** (0.025)	-0.828*** (0.109)	0.317*** (0.025)	-0.620*** (0.114)
Observations	11 855	6 648	11 855	6 648

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table A-2: Control of corruption and hospital policies

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment>0 (2)	Interaction >0 (3)	Log Interaction>0 (4)
Control of Corruption	0.705*** (0.042)	-0.294*** (0.097)	0.705*** (0.042)	-0.116** (0.051)
Hospital Policies	0.621*** (0.031)	0.276*** (0.091)	0.621*** (0.031)	-0.054 (0.059)
Control of Corruption × Hospital Policies	0.958 (0.065)	0.141 (0.089)	0.958 (0.065)	0.042 (0.077)
Observations	11 855	6 648	11 855	6 648

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table A-3: State disclosure policies and control of corruption

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment>0 (2)	Interaction >0 (3)	Log Interaction>0 (4)
Control of Corruption	0.688*** (0.038)	-0.242*** (0.092)	0.688*** (0.038)	-0.077 (0.049)
State Disclosure Policies	0.306*** (0.026)	-0.862*** (0.122)	0.306*** (0.026)	-0.846*** (0.103)
State Disclosure Policies × Control of Corruption	0.910 (0.091)	-0.073 (0.159)	0.910 (0.091)	-0.465*** (0.127)
Observations	11 855	6 648	11 855	6 648

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table A-4: Obligatory and non-obligatory payment acceptance

	Logit (Odds Ratios)					
	Non-obligatory (1)	Obligatory (2)	Non-obligatory (3)	Obligatory (4)	Non-obligatory (5)	Obligatory (6)
Gender (female=1)	0.684*** (0.027)	0.665*** (0.077)	0.681*** (0.027)	0.666*** (0.077)	0.680*** (0.027)	0.666*** (0.077)
Years of practicing medicine in the U.S.	1.063*** (0.003)	1.067*** (0.006)	1.065*** (0.003)	1.067*** (0.006)	1.065*** (0.003)	1.067*** (0.006)
Control of Corruption	0.621*** (0.033)	1.234 (0.173)	0.626*** (0.035)	1.333* (0.201)	0.630*** (0.034)	1.232 (0.175)
Hospital Policies	0.852*** (0.011)	0.972 (0.035)	0.577*** (0.031)	0.789* (0.103)	0.852*** (0.011)	0.974 (0.034)
Hospital Policy × Control of Corruption			1.005 (0.067)	0.797 (0.130)		
State Disclosure Policies	0.282*** (0.022)	0.506** (0.135)	0.318*** (0.025)	0.523** (0.137)	0.282*** (0.024)	0.523** (0.139)
State Disclosure Policies × Control of Corruption					0.930 (0.090)	1.094 (0.308)
Observations	12 175	12 175	12 175	12 175	12 175	12 175

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table A-5: Control of corruption and years of practicing medicine

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment>0 (2)	Interaction >0 (3)	Log Interaction>0 (4)
Control of Corruption	0.548*** (0.053)	0.079 (0.162)	0.548*** (0.053)	0.070 (0.108)
Years of practicing medicine in the U.S.	1.067*** (0.004)	0.087*** (0.007)	1.067*** (0.004)	0.068*** (0.003)
Control of Corruption × Years of practicing medicine in the U.S.	0.996 (0.005)	-0.042*** (0.008)	0.996 (0.005)	-0.025*** (0.005)
Observations	11 855	6 648	11 855	6 648

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table A-6: Combined effect of physician's gender and control of corruption

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment>0 (2)	Interaction >0 (3)	Log Interaction>0 (4)
Control of Corruption	0.686*** (0.045)	-0.312*** (0.105)	0.686*** (0.045)	-0.230*** (0.062)
Female Physicians	0.669*** (0.033)	-0.118 (0.073)	0.669*** (0.033)	-0.144*** (0.052)
Female Physicians × Control of Corruption	0.988 (0.065)	0.175** (0.077)	0.988 (0.065)	0.273*** (0.066)
Observations	11 855	6 648	11 855	6 648

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

APPENDIX B: OTHER CORRUPTION INDICES

Table B-1: Likelihood and size of accepted payments

Total Payments				
	Logit (Odds Ratio)		GLM	
	Payment >0 (1)	Payment >0 (2)	Log Payment>0 (3)	Log Payment>0 (4)
Bribery Incidence	1.012*** (0.003)		0.0003 (0.003)	
Bribery Depth		1.014*** (0.003)		0.002 (0.003)
Hospital Policies	0.757*** (0.015)	0.758*** (0.036)	0.115*** (0.036)	0.116*** (0.036)
Gender (female=1)	0.668*** (0.026)	0.668*** (0.026)	-0.248*** (0.062)	-0.247*** (0.062)
Years of practicing medicine in the U.S.	1.061*** (0.003)	1.061*** (0.003)	0.067*** (0.005)	0.067*** (0.005)
State adopted disclosure policies prior to the Sunshine Act	0.324*** (0.024)	0.325*** (0.024)	-0.831*** (0.111)	-0.834*** (0.110)
Observations	12 979	12 969	7 355	7 350

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table B-2: Hospital policies and corruption indices

Total Payments				
	Logit (Odds Ratios)		GLM	
	Payment >0 (1)	Payment >0 (2)	Log Payment>0 (3)	Log Payment>0 (4)
Hospital Policy Index	0.524*** (0.039)	0.526*** (0.037)	0.201* (0.117)	0.165 (0.112)
Bribery Incidence	1.008*** (0.003)		0.001 (0.003)	
Hospital Policy Index × Bribery Incidence	1.009*** (0.004)		0.001 (0.005)	
Bribery Depth		1.009*** (0.003)		0.001 (0.003)
Hospital Policy Index × Bribery Depth		1.011*** (0.004)		0.004 (0.006)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	12 979	12 969	7 355	7 350

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table B-3: State disclosure policies and bribery indices

Total Payments				
	Logit (Odds Ratios)		GLM	
	Payment >0 (1)	Payment >0 (2)	Log Payment>0 (3)	Log Payment>0 (4)
State Disclosure Policies	0.235*** (0.031)	0.236*** (0.029)	-0.798*** (0.204)	-0.864*** (0.190)
Bribery Incidence	1.009*** (0.003)		0.001 (0.003)	
Bribery Incidence × State Disclosure Policies	1.017*** (0.006)		-0.002 (0.010)	
Bribery Depth		1.012*** (0.003)		0.002 (0.003)
Bribery Depth × State Disclosure Policies		1.021*** (0.007)		0.002 (0.011)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	12 979	12 969	7 355	7 350

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table B-4: Obligatory and non-obligatory payment acceptance, bribery incidence

	Logit (Odds Ratios)					
	Non-obligatory (1)	Obligatory (2)	Non-obligatory (3)	Obligatory (4)	Non-obligatory (5)	Obligatory (6)
Bribery Incidence	1.013*** (0.003)	0.998 (0.007)	1.011*** (0.003)	0.993 (0.008)	1.011*** (0.003)	0.999 (0.007)
Hospital Policies	0.847*** (0.010)	0.938* (0.033)	0.507*** (0.041)	0.609** (0.120)	0.848*** (0.010)	0.939* (0.032)
Hospital Policy × Bribery Incidence			1.006 (0.004)	1.019* (0.010)		
Gender (female=1)	0.683*** (0.026)	0.622*** (0.069)	0.679*** (0.026)	0.626*** (0.069)	0.680*** (0.026)	0.624*** (0.069)
Years of practicing medicine in the U.S.	1.059*** (0.003)	1.058*** (0.006)	1.061*** (0.003)	1.058*** (0.006)	1.060*** (0.003)	1.058*** (0.006)
State Disclosure Policies	0.288*** (0.021)	0.594** (0.148)	0.328*** (0.025)	0.588** (0.144)	0.228*** (0.029)	0.618 (0.253)
State Disclosure Policies × Bribery Incidence					1.015*** (0.006)	0.999 (0.023)
Observations	13 468	13 468	13 468	13 468	13 468	13 468

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table B-5: Obligatory and non-obligatory payment acceptance, bribery depth

	Logit (Odds Ratios)					
	Non-obligatory (1)	Obligatory (2)	Non-obligatory (3)	Obligatory (4)	Non-obligatory (5)	Obligatory (6)
Gender (female=1)	0.682*** (0.026)	0.622*** (0.069)	0.678*** (0.026)	0.626*** (0.070)	0.679*** (0.026)	0.624*** (0.069)
Years of practicing medicine in the U.S.	1.059*** (0.003)	1.058*** (0.006)	1.061*** (0.003)	1.058*** (0.006)	1.060*** (0.003)	1.057*** (0.006)
Bribery Depth	1.014*** (0.003)	1.002 (0.008)	1.012*** (0.003)	0.998 (0.009)	1.012*** (0.003)	1.002 (0.008)
Hospital Policies	0.848*** (0.010)	0.938* (0.033)	0.506*** (0.037)	0.665** (0.118)	0.849*** (0.010)	0.939* (0.032)
Hospital Policy & Bribery Depth			1.007* (0.004)	1.017 (0.010)		
State Disclosure Policies	0.288*** (0.021)	0.593** (0.147)	0.329*** (0.025)	0.585** (0.144)	0.223*** (0.027)	0.640 (0.240)
State Disclosure Policies & Bribery Depth					1.020*** (0.007)	0.996 (0.024)
Observations	13 441	13 446	13 441	13 446	13 441	13 446

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table B-6: Years of practicing medicine and corruption indices

Total Payments				
	Logit (Odds Ratios)		GLM	
	Payment >0 (1)	Payment >0 (2)	Log Payment>0 (3)	Log Payment>0 (4)
Years of practicing medicine in the U.S.	1.049*** (0.005)	1.049*** (0.004)	0.044*** (0.007)	0.043*** (0.006)
Bribery Incidence	1.003 (0.004)		-0.017** (0.007)	
Bribery Incidence × Years of practicing medicine in the U.S.	1.001*** (0.001)		0.001*** (0.0004)	
Bribery Depth		1.003 (0.004)		-0.019** (0.008)
Bribery Depth × Years of practicing medicine in the U.S.		1.001*** (0.000)		0.002*** (0.0005)
Observations	12 979	12 969	7 355	7 350

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table B-7: Female physicians and corruption indices

Total Payments				
	Logit (Odds Ratios)		GLM	
	Payment >0 (1)	Payment >0 (2)	Log Payment>0 (3)	Log Payment>0 (4)
Female Physicians	0.661*** (0.048)	0.806*** (0.061)	-0.422*** (0.089)	-0.394*** (0.084)
Bribery Incidence	1.011*** (0.003)		-0.004 (0.003)	
Bribery Incidence × Female Physicians	1.001 (0.003)		0.010** (0.004)	
Bribery Depth		1.021*** (0.004)		-0.002 (0.003)
Bribery Depth × Female Physicians		0.992** (0.004)		0.010** (0.005)
Observations	12 979	12 969	7 355	7 350

Notes: All models control for the size of the hospital, country characteristics such as per capita GDP (based on purchasing power parity, PPP), the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

APPENDIX C: COUNTRY OF ORIGIN'S PER CAPITA GDP AND BRIBERY INDICES

Table C-1: Correlations between variables

	Control of Corruption	Bribery Incidence	Bribery Depth	GDP per Capita	Regions (World Bank)
Control of Corruption	1	-	-	-	-
Bribery Incidence	-0.704	1	-	-	-
Bribery Depth	-0.670	0.986	1	-	-
GDP per Capita	0.737	-0.664	-0.655	1	-
Regions (World Bank)	-0.286	0.506	0.529	-0.419	1

Table C-2: Size and frequency of payments, excluding GDP per capita

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratio)	GLM	Logit (Odds Ratio)	GLM
	Payment > 0 (1)	Log Payment > 0 (2)	Interaction > 0 (3)	Log Interaction > 0 (4)
Control of Corruption	0.769*** (0.024)	-0.035 (0.053)	0.769*** (0.024)	-0.038 (0.031)
Hospital Policy Index	0.753*** (0.015)	0.119*** (0.036)	0.753*** (0.015)	-0.029 (0.019)
Gender (female=1)	0.675*** (0.026)	-0.232*** (0.063)	0.675*** (0.026)	-0.296*** (0.038)
Years of practicing medicine in the U.S.	1.061*** (0.003)	0.066*** (0.005)	1.061*** (0.003)	0.051*** (0.002)
State adopted disclosure policies prior to the Sunshine Act	0.315*** (0.024)	-0.848*** (0.110)	0.315*** (0.024)	-0.701*** (0.112)
Observations	13 304	7 524	13 304	7 524

Notes: All models control for the size of the hospital, country characteristics such, the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table C-3: Hospital policies and control of corruption, excluding GDP per capita

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment >0 (2)	Interaction >0 (3)	Log Interaction >0 (4)
Control of Corruption	0.794*** (0.030)	-0.071 (0.059)	0.794*** (0.030)	-0.049 (0.035)
Hospital Policy (highly restrictive)	0.596*** (0.026)	0.247*** (0.085)	0.596*** (0.026)	-0.102** (0.047)
Hospital Policy Index × Control of Corruption	0.935 (0.050)	0.083 (0.079)	0.935 (0.050)	0.039 (0.057)
Observations	13 304	7 524	13 304	7 524

Notes: All models control for the size of the hospital, country characteristics such as the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table C-4: State disclosure policies and control of corruption, excluding GDP per capita

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment >0 (2)	Interaction >0 (3)	Log Interaction >0 (4)
Control of Corruption	0.777*** (0.025)	-0.031 (0.054)	0.777*** (0.025)	-0.009 (0.029)
State Disclosure Policies	0.305*** (0.024)	-0.883*** (0.121)	0.305*** (0.024)	-0.929*** (0.092)
State Disclosure Policies × Control of Corruption	0.895 (0.081)	-0.089 (0.152)	0.895 (0.081)	-0.515*** (0.109)
Observations	13 304	7 524	13 304	7 524

Notes: All models control for the size of the hospital, country characteristics such as the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table C-5: Obligatory and non-obligatory payment acceptance, excluding GDP per capita

	Logit (Odds Ratios)					
	Non-obligatory (1)	Obligatory (2)	Non-obligatory (3)	Obligatory (4)	Non-obligatory (5)	Obligatory (6)
Gender (female=1)	0.681*** (0.026)	0.621*** (0.069)	0.677*** (0.026)	0.625*** (0.069)	0.681*** (0.026)	0.621*** (0.069)
Years of practicing medicine in the U.S.	1.059*** (0.003)	1.057*** (0.005)	1.061*** (0.003)	1.057*** (0.005)	1.059*** (0.003)	1.057*** (0.005)
Control of Corruption	0.766*** (0.024)	1.129 (0.084)	0.783*** (0.027)	1.192** (0.100)	0.774*** (0.025)	1.121 (0.086)
Hospital Policies	0.845*** (0.010)	0.942* (0.033)	0.541*** (0.026)	0.795* (0.094)	0.845*** (0.010)	0.942* (0.033)
Hospital Policy × Control of Corruption			0.921 (0.053)	0.817 (0.113)		
State Disclosure Policies	0.287*** (0.021)	0.573** (0.142)	0.325*** (0.025)	0.566** (0.139)	0.277*** (0.022)	0.577** (0.144)
State Disclosure Policies × Control of Corruption					0.897 (0.082)	1.127 (0.263)
Observations	13 304	13 304	13 304	13 304	13 304	13 304

Notes: All models control for the size of the hospital, country characteristics such as the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table C-6: Years of practicing medicine and control of corruption, excluding GDP per capita

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratios)	GLM	Logit (Odds Ratios)	GLM
	Payment >0 (1)	Log Payment >0 (2)	Interaction >0 (3)	Log Interaction >0 (4)
Control of Corruption	0.634*** (0.055)	0.473*** (0.171)	0.634*** (0.055)	0.282*** (0.094)
Years of practicing medicine in the U.S.	1.070*** (0.004)	0.088*** (0.007)	1.070*** (0.004)	0.068*** (0.003)
Control of Corruption × Years of practicing medicine in the U.S.	0.983*** (0.005)	-0.053*** (0.008)	0.983*** (0.005)	-0.036*** (0.005)
Observations	13 304	7 524	13 304	7 524

Notes: All models control for the size of the hospital, country characteristics such as the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

Table C-7: Physician's gender and control of corruption, excluding GDP per capita

	Total Payments		Frequency of Interactions	
	Logit (Odds Ratio)	GLM	Logit (Odds Ratio)	GLM
	Payment >0 (1)	Log Payment >0 (2)	Interaction >0 (3)	Log Interaction >0 (4)
Control of Corruption	0.770*** (0.031)	-0.025 (0.067)	0.770*** (0.031)	-0.068* (0.039)
Female Physicians	0.674*** (0.028)	-0.241*** (0.067)	0.674*** (0.028)	-0.269*** (0.043)
Female Physicians & Control of Corruption	0.996 (0.051)	-0.027 (0.067)	0.996 (0.051)	0.081 (0.052)
Observations	13 304	7 524	13 304	7 524

Notes: All models control for the size of the hospital, country characteristics such as the region where the country of origin is located, as well as year fixed effects. Robust standard errors in parentheses $*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$

APPENDIX D: FOREIGN-TRAINED PHYSICIANS AND COUNTRIES OF ORIGIN

Table D-1: Average payments, number of physicians and country of origin's corruption indices

Country Name	Number of Physicians	Average Annual Interactions Per Physician	Average Annual Payments, Per Physician	GDP Per Capita (PPP)	Bribery Depth (%)	Bribery Incidence (%)	Control of Corruption
Afghanistan	1	0.2	2.9	1 437.9	34.6	46.8	-1.51
Albania	5	1.2	70.5	7 514.8	16.7	19.5	-0.67
Algeria	3	9	180.9	11 343.7	N/A	N/A	-0.55
Anguilla	1	0.4	90.4	N/A	N/A	N/A	1.24
Antigua and Barbuda	1	212.2	9285.7	18 414.5	6.4	6.9	1.15
Argentina	20	19.2	429.5	15 744.3	7.1	9.3	-0.39
Armenia	6	34	1007.2	5 548.4	6.1	7.1	-0.66
Aruba	1	4.2	67.5	35 973.8	N/A	N/A	1.19
Australia	2	0.1	5.5	35 925.2	N/A	N/A	2.01
Austria	3	0.1	7.9	38 671	N/A	N/A	1.76
Azerbaijan	7	52.4	922.5	10 734.9	13.8	15.9	-1.15
Bahrain	1	0.2	3	39 602.1	N/A	N/A	0.26
Bangladesh	38	9.2	163.2	2 122.38	43.9	47.7	-1.16
Barbados	112	19.4	420.3	14 968.9	1.1	1.2	1.47
Belarus	14	32.2	761.4	12 319.6	4.4	8.9	-0.66
Belgium	11	54.9	1933.9	36 121.7	N/A	N/A	1.44
Belize	2	3.1	103.6	7 081.5	6.2	6.2	-0.25
Bolivia	2	11.7	186.1	4 871.8	6.4	9.1	-0.59
Bosnia and Herzegovina	1	0.6	32.2	7 823.9	7.8	10.7	-0.33
Brazil	12	1.5	43.7	12 322	8.4	11.7	-0.02
Bulgaria	10	27.3	475.6	12 177.7	6.4	8.9	-0.13
Canada	21	14.6	355.5	37 121.6	N/A	N/A	1.97

Cayman Islands	10	12.3	275.8	49 903	N/A	N/A	1.2
Chile	2	58.4	956.5	15 844.4	0.8	1.3	1.45
China	85	19.1	464.5	7 576.8	9.9	11.6	-0.53
Colombia	28	22.3	994.9	9 667.4	5	6.6	-0.25
Costa Rica	13	7	256	11 367.3	6.6	8.7	0.57
Croatia	5	19.2	433.9	16 990.5	2.5	3.9	0.08
Cuba	11	18.1	429.6	N/A	N/A	N/A	0.27
Czech Republic	6	7.8	152.3	24 536.7	N/A	N/A	0.36
Denmark	1	0.4	38.1	37 975.1	N/A	N/A	2.4
Dominica	6	36.1	549.9	8 682.1	4.8	5.8	0.67
Dominican Republic	64	29.5	656.1	9 588.7	11	12.3	-0.75
Ecuador	10	21.2	889.1	8 456.5	4.5	5.9	-0.72
Egypt	68	25.1	446.7	8 176.2	13.6	15.2	-0.67
El Salvador	1	0.2	6.9	5 798.4	2.3	4.2	-0.35
Estonia	2	44.9	999.9	19 109	0	0	1.02
Ethiopia	34	5.9	91.7	909.5	19.8	26.8	-0.68
Fiji	1	6.8	104.6	6 883.29	6.7	10.5	-0.14
France	11	17	315.9	32 968.8	N/A	N/A	1.44
Georgia	10	4.6	98	5 640.1	1.3	2.2	-0.05
Germany	16	3.9	91.7	36 344.9	N/A	N/A	1.79
Ghana	19	10.4	155.4	2 760. 1	14.7	18.7	-0.09
Greece	7	7.3	129.9	25 237.6	N/A	N/A	0.15
Grenada	123	22.5	635.6	10 291.6	3.8	6.6	0.47
Guatemala	2	0.3	9.6	6 117.6	1.5	2.8	-0.64
Guyana	1	0	0	5 183.7	8.7	14.9	-0.58
Haiti	9	35	793.9	1 503.9	N/A	N/A	-1.26
Hong Kong	4	4.3	91.5	40 845.9	N/A	N/A	1.86
Hungary	17	25.3	501.4	18 881.4	1.1	2.1	0.52

India	210	11.8	477.8	3 645	19.6	22.7	-0.42
Iran	34	2.6	113.9	14 777.1	N/A	N/A	-0.68
Iraq	31	39.9	868.9	11 691.5	33.8	37.3	-1.36
Ireland	18	6.2	101.4	42 950.1	N/A	N/A	1.62
Israel	27	7.4	141.8	28 111.2	0	0.1	0.87
Italy	60	41.2	1432.9	32 302.8	N/A	N/A	0.27
Jamaica	5	14.7	305.1	7 569.7	17.9	19.3	-0.27
Japan	4	0.8	25.5	33 080.6	N/A	N/A	1.39
Jordan	13	4.8	206.5	7 931.7	10.4	12.7	0.2
Kazakhstan	1	6.8	196.9	16 440.8	22	26.7	-0.99
Kenya	8	1.9	38.6	2 237.6	16.7	26.4	-0.98
Kyrgyzstan	2	0.6	8.9	2 450.2	53.6	59.8	-1.23
Latvia	4	19.6	497.1	16 003.3	2.3	3.5	0.28
Lebanon	14	18.9	293.1	12 627	14.3	19.2	-0.81
Liberia	1	0	0	663.3	41.5	56.1	-0.76
Libya	11	1.5	26.8	20 829.9	N/A	N/A	-1.12
Lithuania	7	8.7	241	17 851.9	9.8	10.4	0.28
Macedonia	1	14.2	365.8	9 411. 3	3.9	7.5	-0.25
Malaysia	1	6	254	18 651.2	21.9	28.2	0.13
Mexico	96	22.9	488.2	13 706.8	9.6	17.6	-0.31
Moldova	2	11.3	277.8	3 355.7	22.2	31	-0.69
Morocco	3	0.27	11.64	5 511.8	29.5	37.2	-0.33
Myanmar	25	24.3	390.4	2 859.6	26.7	29.3	-1.56
Nepal	25	8	172.7	1 729.3	10.9	14.4	-0.77
Netherlands	3	19.6	284.7	40 512.4	N/A	N/A	2.09
New Zealand	1	0	0	28 816	N/A	N/A	2.32
Nicaragua	3	31.1	715.2	3 756.3	4	6.5	-0.69
Nigeria	79	9.8	201.6	4 110.2	26	28.9	-1.11

Norway	2	1	44.9	50 875.1	N/A	N/A	2.05
Pakistan	203	11.9	227.2	3 811.1	28.5	30.8	-1
Panama	6	0.9	19.1	13 824.5	6.7	7.1	-0.29
Paraguay	3	71.5	897	6 489. 9	9.3	13.8	-1.01
Peru	13	13.4	558.2	8 385.5	11.5	17.6	-0.27
Philippines	118	21.1	556.9	4 957.1	12.4	17.2	-0.7
Poland	43	20.2	327.8	17 582.3	1.8	1.9	0.4
Portugal	2	3.5	43.9	24 165	N/A	N/A	1.07
Romania	60	9.7	190.4	13 437.5	6.1	9.8	-0.22
Russia	68	27.2	647.7	16 221.4	9.7	14.2	-1
Saint Kitts and Nevis	2	2.8	50.5	20 111.9	N/A	N/A	0.89
Samoa	1	24.4	445	4 853.9	22.4	30.5	0.16
Senegal	1	2	81.7	1 953.2	8.6	11.1	-0.37
Serbia	8	4.8	88.2	10 081.3	4.5	6.1	-0.34
Sint Martin	38	15.9	274.4	36 327.2	N/A	N/A	N/A
Slovakia	1	18.2	196.2	20 280.9	4	4.4	0.33
South Africa	11	3.8	77.4	10 390.1	3	4.2	0.24
Spain	12	66.4	1203.5	28 915.7	N/A	N/A	1.17
Sri Lanka	16	5.8	107.3	7 335.7	9.2	10	-0.28
Sudan	14	26.4	668.1	3007.6	7.6	17.6	-1.29
Sweden	1	0.8	35.2	37 880.4	1.5	1.9	2.21
Switzerland	1	0	0	47 912.5	N/A	N/A	2.08
Syria	56	17.1	289.2	N/A	N/A	N/A	-1.06
Taiwan	3	9.7	301.6	N/A	N/A	N/A	0.68
Tajikistan	5	53	910.9	1 785.8	29.6	36.3	-1.19
Thailand	1	0.4	42.8	11484.5	8.7	9.9	-0.32
Turkey	12	6.4	114.4	15 395.3	2.5	5.4	0.04
Uganda	2	0	0	1 279.5	14.6	22	-0.86

Ukraine	38	42.9	1049.9	6 634.7	44.7	50.4	-0.92
United Arab Emirates	1	10.8	182.9	72 282.1	N/A	N/A	1.01
Uruguay	3	4.1	75.1	14 463.6	2	2.4	1.2
Uzbekistan	12	47.3	1225.9	3 593.3	4.6	7	-1.19
Venezuela	14	18.4	1220.6	14 343.3	5.5	10.3	-1.13
Vietnam	4	46.5	847.8	3 693	21.7	26.1	-0.65
Zambia	1	1.4	98.6	2 671.7	9.7	15.8	-0.46
Total (113)	2905						

Table D-2: Foreign-trained physicians serving U.S. population, by per-capita income

Per-capita Income (USD)	Total Population	Number of Physicians per 1000 Residents	Total Number of Physicians	Foreign-trained Physicians	
				Number	Percent (%)
0-15 000	8 016 043	1.9	15 413	6 557	42.5
15 001-20 000	45 370 184	1.9	87 097	26 049	29.9
20 001-30 000	162 286 815	2.3	370 891	93 574	25.2
30 001-40 000	58 032 770	4.1	237 978	57 439	24.1
40 001-50 000	18 345 488	6.6	120 633	28 446	23.6
50 001 or more	9 370 897	10.7	100 650	24 257	24.1

Source: American Immigration Council, 2018