Title
Conflict of Interest and Incentives in Health Care

Author
Parker, Sara E.

Publication Date
2013

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Conflict of Interest and Incentives in Health Care

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Management

by

Sara E Parker

2013

ABSTRACT OF THE DISSERTATION

Conflict of Interest and Incentives in Health Care

by

Sara E Parker

Doctor of Philosophy in Management

University of California, Los Angeles, 2013

Professor Marvin Lieberman, Co-Chair

Professor Subramaniam Ramanarayanan, Co-Chair

This dissertation explores conflicts of interest and incentive schemes in the health care industry. Chapter 1 explores internal conflicts that a firm may unwittingly introduce itself. Even when perverse incentives do not exist, the introduction of additional activities or tasks may create a conflict at the operational level by undermining the firm's ability to perform its primary task. I will examine this question in the setting of kidney transplant centers by estimating the effect of diversification into liver transplants on the risk-adjusted mortality rates of kidney transplant recipients. The results suggest diversification in general increased the risk adjusted mortality rate, but this increase was largely offset for older patients who tend to have more comorbidities. That is, diversification did not present a conflict for patients whose own health issues tend to be "diversified," while it did present a conflict for others. Further, the effect of diversification was significantly larger for smaller centers. This suggests

that a given firm's patient (or customer) mix and characteristics may draw the line between what is a conflict for the firm, and what is not.

Chapters 2 and 3 examine external conflicts of interest in the form of perverse incentives. Payments from pharmaceutical manufacturers to physicians typify the type of complex conflict of interest relationship that many types of firms may face. Such payments may create value for the company in the form of drug samples, financing trainings, etc, but they may also capture value away from the firm by inducing physicians to prescribe more (and more expensive) drugs. Chapter 2 examines whether disclosure of such payments has any effect on physicians' prescribing behavior. I exploit a natural variation in the timing of disclosures for Pfizer, in which payments can be observed but physicians were not aware that they would be disclosed that in turn enables estimation of the effect of disclosure on physician behavior using a differences-in-differences approach. The results indicate that while the post-disclosure period was associated with a decline in the number of prescriptions overall, physicians whose names had been disclosed as having received payments actually slightly increased the rate at which they prescribe branded drugs. Chapter 3 then explores whether there is concrete evidence that such payments to physicians have a persuasive effect on physicians, rather than an informational effect or simply reflecting the physician's existing preferences. This analysis relies on another natural experiment: in 2010, pharmaceutical company GlaxoSmithKline announced their intention to cut the number of physicians they were paying, unrelated to any changes in their product offerings. I use this cut to examine the effect on physicians, demonstrating that these physicians significantly altered their prescribing behavior.

The dissertation of Sara E Parker is approved.

Florian Ederer

Timothy Groseclose

Marvin Lieberman, Committee Co-Chair

Subramaniam Ramanarayanan, Committee Co-Chair

University of California, Los Angeles

2013

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

VITA

Sara E Parker

EDUCATION

University of California, Los Angeles
M.A. in Economics, June 2010

Wellesley College
B.A. in Honors International Relations, magna cum laude, September 2001—June 2005

PREVIOUS EMPLOYMENT

McKinsey and Company, June 2005 – July 2008

PUBLICATIONS

Co-Author/Contributor:
"How health care costs contribute to income disparity in the United States." *McKinsey Quarterly*, April 2009.
"Addressing Japan's health care cost challenge." *McKinsey Quarterly,* May 2008.
"The Challenge of Financing Japan's Future Health Care Needs." *McKinsey Global Institute Report*, May 2008.
"Accounting for the Cost of Health Care in the United States." *McKinsey Global Institute Report*, July 2006.

MEMBERSHIPS

Academy of Management
American Society of Health Economists

CHAPTER 1: TRANSPLANT CENTERS AS FOCUSED FACTORIES

I. INTRODUCTION

How diversified should our health care providers be? Hospitals that provide the full panoply of health services have such a long history as the "home" of medicine that one might think that this question is simply rhetorical. General hospitals, however, face increasing threats from smaller, specialist providers. Some health care reformers maintain that the general hospital model of "all services for all patients" best serves neither patients nor hospitals, and that specialty clinics can achieve better outcomes at lower costs. Still others allege that these specialty facilities add no value, and are only selectively admitting the most profitable, least risky patients. The provision of health care in the United States concerns over 300 million lives and $2.3 trillion dollars[1], and thus the resolution of these questions should not be left to rhetoric. Despite the import of this topic for the health care industry, patients, and governments, surprisingly few rigorous studies of the impact of diversification on hospital performance have been done and the results of the impact of specialization versus diversification have been, overall, inconclusive.

In addition to the implications for the health care industry in particular, the question of health care diversification has important implications for strategic management theory as well. Supporters of increasing specialization in the health care industry appeal to the idea that hospitals must become "focused factories." Skinner introduced the concept of the focused factory to address the industry malaise of U.S. manufacturing in the 1970s (Skinner, 1973). Simply put, he posited that performing a single task, focused around the product and the customer segment, would allow workers to develop internally consistent routines and

[1] 2008 National Health Expenditures.

protocols, minimizing inconsistencies and thus improving performance. Conversely, diversification into multiple product lines or customer segments within the same factory introduces inconsistencies into the manufacturing process—diversity of tasks limits the ability of workers to develop routines through the repeated performance of a single, specific task. It is not at all clear, however, whether these findings hold across industries. Is the idea of "factory focus" a general strategy concept, or must it be confined to the manufacturing sector?

The related diversification literature presents an alternative viewpoint, still in many ways consistent with factory focus, but extrapolated to any type of firm. This view of diversification predicated not on the anatomy of a manufacturing task, but on the core strategy of the firm. This literature puts forth that it is not diversification per se that is detrimental to a firm, but diversification into unrelated businesses (Rumelt, 1982). If a firm diversifies into a business that also fits with the core strategy, leverages its existing strategic assets and enhances rather than impedes learning, then diversification should have a positive impact on performance. Thus we should only expect focus to be a superior strategy for a given firm when diversification does not satisfy these criteria. The combination of diversification with focus allows a continuum of classification: specialized/focused, coherently diversified, incoherently diversified. The question of whether it is preferable for a firm to be focused or diversified is simple to observe. Failing to separate individual firm effects of relatedness, however, can confound the observed effect of diversification, overstating the importance of focus.

I will address the question of the impact of diversification on outcomes using data on kidney transplant centers, compared with outcomes at centers that also diversify into liver transplants. This setting is a natural place to test the differential impact of focus, related diversification, and unrelated diversification. In medicine in general, and surgeries in particular, individual and team learning are crucial, protocols and routines can develop quickly (Edmondson et al, 2001; Inman et al, 2005) and training on too many protocols can be detrimental to the quality of care (Inman et al, 2005). Similar to a factory floor where complex sets of tasks can cause coordination difficulties that result in defects, coordination of clinical staff and facility resources can become more difficult with increasing variety (Kraus et al, 2005). Yet if this variety can yield experience that is complementary to a particular hospital's extant skill-base—whether those skills are clinical expertise, facility coordination, administrative efficiency, or any other mechanism—rather than merely distracting from it, then diversification could improve performance.

Examining kidney and liver transplant centers provide an excellent setting in which to test this: the surgeries are sufficiently similar to suggest that adding livers could enhance organizational learning without distracting from the center's core mission. On the other hand, liver surgeries require more expertise than kidney surgeries, and thus the introduction of additional complexity may be detrimental to the center's performance. Within general hospitals, wholly unrelated activities such as psychiatric care are unlikely to be co-located, so any effect of focus on operations is difficult to interpret in the context of the focused factory mechanism. The possibility of direct impact, either positive or negative, on the activities within the unit thus makes a transplant center a particularly informative setting.

I employ the related diversification rubric of Teece, Rumelt, Dosi and Winter (1994) to generate predictions as to whether diversification or focus is preferable given the characteristics of the market overall. Market-level inefficiencies, such as hospital reluctance to close down poorly performing centers, will lead to inappropriate diversification. This inappropriate diversification will cause a detrimental relationship between diversification and outcomes, as measured by patient mortality within a year of transplant. Firms may vary widely, however, on other dimensions that could affect whether diversification suits their core strategy or not; whether diversification is coherent or not may not apply to all transplant centers. I will examine the effect of diversification in conjunction with firm level characteristics that may impact the mechanism by which a firm is benefitted or harmed by diversification.

And finally, the factory focus literature defines focus around the inputs of production; related diversification focuses on the market setting, and thus does not address focus vs. diversification at this level. In this setting the inputs of production are, in a sense, also the consumers of their service—the patients and donors. This adds a complication that neither related diversification nor factory focus allows for. That is, different firms may have access to different types of inputs of production, and what is more, in this setting the firms (i.e., transplant centers) have may not exercise control over these inputs. Patients ultimately make the decision where to have their transplants performed, and in this respect may alter a hospital's relative benefit from diversification. Thus I will also expand analysis to examine the effects of diversification by patient characteristics.

I will use data on all kidney and liver transplants performed in the United States between 1988 and 2007, provided by the United Network for Organ Sharing. By aggregating these data, including patient characteristics, by center and market it will be possible to observe the impact of diversification both in isolation and with respect to the firm and patient characteristics that may impede or enhance a firm's ability to benefit from focus. I find that diversification is associated with inferior outcomes overall, but these effects differ significantly by firm size, over time, for older patients, and for patients with poorer donor matches. Thus diversification is indeed detrimental, and focus preferable, for some firms. The results presented here do not, however, support blanket recommendations of focus for all providers. One important consideration for this type of setting is selection; particularly since we do not observe the financial performance of these centers, it is crucial to control for the possibility that the effect of diversification is a symptom of the types of firms that choose to diversify, rather than the cause. The results presented here are robust to the inclusion of multiple types of selection controls.

A major contribution of this paper is to examine the firm specific characteristics that predict the comparative disadvantage (or lack thereof) garnered by a lack of focus. The medical setting in general and these data in particular provide a uniquely rich resource of characteristics of both firms and "inputs" (in this case, patients) which no other industry can provide. A key element of this contribution stems from the particular richness of the dataset used here. By analyzing the universe of accredited firms in this industry, rather than a sample, much more precise conclusions can be reached regarding the determinants of the negative ramifications of diversification. These determinants contribute to the empirical literature through improved measurement and predictive power of the diversification effect, while also enabling further study to elucidate more precisely the mechanism by and contexts in which diversification affects firm performance.

By examining the differential impact of diversification by firm and input characteristics, this paper also adds an important insight to the focused factory/related diversification literature. Namely, these results demonstrate that the types of patients a hospital sees are an important determinant of whether one could consider diversification as coherent with firm strategy or not. These results highlight the importance and relevance of manufacturing-type concerns even within a service industry, particularly in industries such as health care and education where consumers are also the inputs to production. In industries where consumers are also the inputs to production, a "focused diversification" strategy may be preferable for some firms. In the current health policy discussion of focus, the current blanket approach – assuming that diversification is strictly worse for all settings, patients and diseases—goes too far in the other direction and risks inappropriate specialization where diversification may have been preferable.

The paper proceeds as follows: Section II reviews the relevant literature and derives hypotheses with respect to this setting. Section III describes the data analyzed, including the dynamics of the transplant market. Section IV presents the specifications designed to test the hypotheses from Section II, and Section V presents the results. Section VI concludes.

II. Literature Review and Hypotheses

In 1974, Wickham Skinner called American manufacturers to focus rather than expand their operations; that

> because its equipment, supporting systems, and procedures can concentrate on a limited task for one set of customers, [a focused factory's] costs and especially its overhead will be lower than that of a conventional plant. But, more important, such a plant can become a competitive weapon because its entire apparatus is focused to accomplish the particular manufacturing task demanded by the company's overall strategy and marketing objective" (Skinner, 1974).

The concept of the focused factory is largely predicated on the idea that "simplicity, repetition, experience, and homogeneity of tasks breed competence." He clarifies that focused factories do not necessarily require separate plants, but rather firms can develop a "plant-within-a-plant […] in which the existing facility is divided both organizationally and physically." Naturally, much research has been conducted based on these ideas since Skinner's original publication. Subsequent research can largely be classified into three subtopics: fit ("a company's manufacturing system should reflect its competitive position and strategy"), focus ("a means to achieve this fit and a discipline for maintaining it in the face of the continual barrage of potentially distracting opportunities") and organizational learning (Hayes and Pisano, 1996).

An alternative viewpoint emerges from the related diversification literature. Although the focus literature allows for a variety of dimensions along which a factory can focus its operations, the general view is that complexity is antithetical to performance. The related diversification literature suggests, however, that "a firm may exhibit coherence though it may not necessarily be specialized" (Teece et al, 1994). From this perspective, a firm may benefit from diversification to the extent that operating in related industries: enhances firm learning; generates future opportunities that would not otherwise be available due to path dependencies; and enables access to or development of strategic assets (Teece et al, 1994; Markides and Williamson, 1994). If related businesses can both leverage and contribute to a firm's core competence (Teece, 1988), the diversified firm should have an advantage over an undiversified firm. Employing the Teece et al (1994) framework, one should expect to see specialist firms when learning is rapid, technological opportunities are rich, and future opportunities are highly path dependent.

Although they may at first blush seem wholly disparate, factory focus and related diversification are in fact very similar at the core. Both theories posit that successful firms will only pursue those tasks that are coherent with their strategy. Skinner believed that "each strategy creates a unique manufacturing task"; Markides and Williamson (1994) point out that "relatedness" should be determined not by the industry, but by its contribution to a firm's strategic assets, and thus diversification should occur to the extent that it still serves the same strategy. One discrepancy arises from the belief that a given strategy will uniquely define a single task or a variety of tasks. Another discrepancy between these theories is the question of the mechanism and unit of analysis. Related diversification is thought to increase the market power of the parent company and improve profitability. Factory focus, on the other hand, posits that performing multiple activities in the same facility will cause "inconsistencies and conflicts" and thus harm performance within a business unit (Skinner, 1974).[2] It is assumed that the skills of an organization lie in its routines (Nelson and Winter, 1982), and that employees are able to perform these routines more effectively when they have fewer routines to learn (Edmondson et al, 2001).

Despite these discrepancies, distinguishing between the theoretical predictions of related diversification and the focused factory literature in empirical work has proved to be a thorny problem. Empirical findings in the focused factory literature suffer from difficulties similar to the diversification discount literature: the effect is identified without being able to fully appreciate the mechanism (such as in Schoar, 2002). Neither literature can identify the mechanism exactly by looking at cross-sectional performance or an individual case study (Leong et al, 1990). As a result, more recent work in both the operations literature (Mukherjee et al, 2000) and the health care strategy literature (Clark and Huckman, 2009) has focused on elucidating these mechanisms by demonstrating the particular features of a firm

[2] This mechanism is also the primary distinguishing feature between the focused factory literature and the much larger literature on the diversification discount. In the diversification discount literature, the focus is on conglomerates acquiring a new business unit, rather than adding activities within existing operations. Ultimately the conclusions reached by the diversification discount and focused factory literatures are broadly the same—that increased diversity worsens firm performance—but the settings and hypothesized mechanisms differ.

setting where either focus or related diversification may have a more beneficial effect than the other on outcomes.

Related diversification is essentially the status quo in the hospital industry, where specialty hospitals are still relatively rare, and most hospitals provide most types of health services. Recent increases in the number and share of specialty hospitals (Shactman, 2005) have coincided with scholarship that seeks to apply the focused factory model to health services. Given that the focused factory concept is based on manufacturing, its popularity in health care literature may be surprising. Health care is a service that requires extensive training for its practitioners even at the administrative level, not a repetitive manufacturing task; care is not a commodity that can be stocked, and thus production control processes must differ from manufacturing firms (De Vries, Bertrand, Vissers 1999); and service outcomes and productivity may be more difficult to analyze, as they may be "fuzzier" than in manufacturing (Roth and Menor, 2003). Other authors, however, have argued that factories and hospitals are more alike than they are different (Torrance in Coburn et al 1998, Lega and Depietro, 2005). Particularly in certain specialties such as surgery, there are clear parallels between operations strategy in manufacturing and health service contexts. The case has been made many times over for the application of the focused factories idea to health care settings—a large share of the empirical evidence on focus comes from health care industry (Huckman and Zinner, 2008).

Although the topic of focus has been broadly applied to health care, it has not been applied consistently. By far the most popular applications have been case studies of hospitals that are highly specialized, focused from the perspective of both customer segment and hospital routine, such as the Shouldice Hospital of Ontario which only performs inguinal hernia surgeries. One of the key proponents of this view, Regina Herzlinger, maintains that focused factories could be organized according to a single procedure (she cites a hospital that performs only cataract surgeries) or a single diagnosis, such as cancer. Hyer et al (2009) lend some formality to the case approach, examining an implementation of focus in a trauma center, finding no impact on mortality, but improvement in the operating margins. In their review of other work, they note that in general the impact of specialization in hospitals is difficult to assess given the lack of truly rigorous work in this field.

The lack of rigorous work may be at least partly attributable to lack of clarity in defining focus (Huckman and Zinner, 2008; Hyer et al, 2009; Shactman, 2005). Authors within the operations literature have treated hospitals as "virtual organizations," composed of distinct clinics for each specialty. Thus even an "unfocused" hospital could be considered an example of a plant-within-a-plant. This lack of clarity can make it difficult to draw inferences even from the most rigorous work. For instance, Huckman and Zinner (2008) found that focus within an organizational unit improved output in clinical trials. In contrast, Clark and Huckman (2009) find little support for any impact of focus but rather demonstrate evidence for complementary spillovers within multi-unit firms, that is "multi-unit firms with a portfolio of related businesses outperform both single-unit firms and multi-unit firms." In order for this field to advance, it will be necessary to clearly delineate what type of focus is being addressed, and the features of the setting that may make focus versus related diversification a superior strategy.

To a certain extent, the diversity of definitions of focus is unavoidable, in that there is no single, precise definition. Skinner (1974) notes a variety of different dimensions along which a firm can choose to focus, depending on its strategy; subsequent research has noted that focus along a single dimension may cause conflicts and lack of focus along other dimensions[3] (Mukherjee et al, 2000). Secondly, some of the heterogeneity in findings in this field will be driven by the inherent heterogeneity of the health care industry— the service performed by a neurosurgeon bears very little resemblance to that rendered by a pediatrician, and thus it should not be surprising if the optimal organizational form of these units differed. This is not to say that a coherent application of the theory of the focused factory is impossible. On the contrary, it is simply necessary to be clear on what type of setting and focus one is addressing. Returning to the general theoretical setting, related diversification generally employs industry as the measure of relatedness, where characteristics of the industry are used to predict the diversification of its constituent firms. Markides and Williamson (1994) and Skinner (1974) both emphasize diversification and specialization (respectively) as it serves the individual firm's strategy. Thus, to make empirical predictions about the impact of diversification, one needs to address whether it makes sense in the context of the industry overall, and given a particular firm's characteristics and strategy.

In this paper, I will examine the impact of process-defined focus in the setting of kidney transplant centers. The natural outcome measure in surgeries in general, and transplant surgeries in particular, is the risk-adjusted mortality rate; these statistics are the de facto quality measurement of transplant programs in both clinical and consumer literature. Whether process-focus is the most appropriate type of focus for this setting will be addressed by the findings. It may be, as in Clark and Huckman (2008), that surgeons would benefit more from related diversification defined by patient co-morbidity. In this case, however, transplant surgeons are trained to do all types of organ transplants, and thus it is appropriate to

[3] General dimensions of focus can include: product, process, market segment, geography, volume and suppliers.

test if this type of diversification among patient types but not among procedures is beneficial or detrimental at the center level.

I will contrast transplant centers that perform kidney but not liver transplants with centers that perform both kidney and liver transplants. While these centers may perform as many as 8 transplant types, livers and kidneys account for 80 percent of all transplants. Heart and lung transplants account for an additional 15 percent. I compare the addition of liver transplant programs rather than all other programs because the possibility of diversification having an impact on the kidney program, whether positive or negative, will be significantly more likely when adding a surgery center for which the transplants are more similar (as in livers). Technologies and skills are more similar to kidney transplants for liver transplants[4] than for heart or lung transplants; thus the possibility of benefits from related diversification, or diseconomies due to distraction or coordination difficulties from sharing facilities and equipment, are more probable.

As discussed before, we would expect firms to be specialized in markets where future opportunities are highly path dependent, technological opportunities are rich, and learning is rapid. Learning and technological opportunities may not be as informative in a medical context, given the incentives in place for broad dissemination of learning and technological advances (Lomas, 1993; McKinlay, 1981). Another feature that Teece et al employ to categorize markets is selection. From a purely economic standpoint, reimbursement in the

[4] For instance, laparoscopic techniques are more common in kidney transplants, but have recently been deployed in liver transplants as well: http://www.georgetownuniversityhospital.org/body.cfm?xyzpdqabc=0&id=413&UserAction=PressDetails&action=detail&ref=176

transplant market is both complex and uncertain,[5] and many hospitals do not even know whether their own centers are profitable (Abecassis, 2006). Transplant centers are popularly viewed as a source of prestige for hospitals (Levine, 2006), particularly centers with multiple transplant types (DHHS Report, 2003) and thus hospitals may be reluctant to close down even poorly performing programs. These market inefficiencies give ample opportunity for diversification that serves the interests of neither the patients nor the hospitals themselves. Even in the absence of market inefficiencies, there is reason to believe that diversification may be detrimental to outcomes: as noted previously, related diversification has been viewed as a source of market power that allows firms to increase their profitability (Palepu, 1985); in the context of health care, however, it has been argued that firms that compete at the level of individual patients and treatments will add more value than firms that compete based on bargaining agreements and market power (Porter, Teisberg, 2004). Thus there are multiple mechanisms by which one might argue that focus will produce clinical outcomes superior to those achieved by diversified firms.

The final factor, organizational learning, yields a clearer prediction than path dependencies or technological opportunities. It is widely accepted in the field of surgery that learning is linked to volume of procedures performed—in order to qualify for Medicare reimbursement, a center must perform a minimum number of transplants per year, varying by the difficulty of the transplant type. The gains to learning-by-doing are increasing although not strictly linear, both at the hospital level (Luft, Bunker, Enthoven, 1979) and the physician level (Ramanarayanan, 2008). The effect of diversification on learning, however, is not entirely clear: if the addition of a liver transplant program provides surgical teams with

[5] The costs incurred and reimbursement given cannot be known before the surgery, as much of this will be determined by complications. For surgeries with extreme complications, providers may it a reimbursement ceiling beyond which they cannot recoup their costs.

additional experience, then diversification may be beneficial. If, however, the addition of a liver transplant program directs resources away from the kidney program (Noda and Bower, 1996; Hill et al, 1992), increases coordination costs or difficulties by increasing the caseload (Chirikos and Sear, 2000), or results in increased workload for the staff (Tarnow-Mordi et al, 2000), mortality will increase. Given that the learning-by-doing literature has generally demonstrated that in surgery, surgical experience on a particular procedure reduces mortality rates, but general surgical experience does not (Choti et al, 1998; Swisher et al, 2000), one would expect:

Hypothesis: diversified firms will have inferior clinical outcomes.

In order to understand more precisely the nature of this effect, I will test this hypothesis in a variety of extensions in order to help clarify the mechanism by which the main effect occurs.

Neither focus nor related diversification literatures in the health care field suggest any heterogeneity by firm characteristics in the effect of diversification. But if we take learning to be the mechanism by which diversification affects outcomes, then we would expect certain features of the firm to have a large impact on whether diversification will cause distraction, coordination difficulties, overwork, or other potential difficulties that may prevent the formation or inhibit the execution of routines. In particular, at the center level volumes may play a role, not just in learning, but in operational performance as well. Hospital size has been demonstrated to have a non-linear effect on efficiency, in that medium-to-large size firms are on average less efficient than the largest or smallest (Ozcan et al, 1992)[6]. Centers

[6] Although it is not reflected in the literature, average length of stay (ALOS) in a center may also be viewed as a proxy for its relative efficiency. However, none of these specifications were significant and thus are omitted.

that already have below average efficiency will likely experience an even greater detrimental effect from diversification:

Extension 1: the impact of diversification on clinical outcomes will vary non-monotonically in firm size.

The extent to which firm size will have an impact is likely related to a variable that this study, as well as most other studies based on panel datasets, omits: degree of diversification. In a transplant center, this may vary significantly. For instance, at the UCLA transplant center, the personnel who deal with kidneys versus livers are completely separate, with the exception of one consulting physician. Otherwise, from the transplant surgeon to the nurses to the social workers who follow up with transplant recipients, the teams are completely separate. At the largest centers, it is unlikely that diversification could cause any distractions, coordination problems, or inefficiencies because the presence of additional transplant programs has very little impact on any other program, while at smaller centers there will be a single transplant surgeon for both kidney and liver transplants. Unfortunately, while center size and degree of integration do appear to be related, there is insufficient evidence on either the precise nature of the relationship or the direction of causality to make any inferences from it. In the absence of a measure of the actual extent of integration, estimates from this model should be regarded as a lower bound in terms of the impact of diversification on outcomes.

Patient composition is also an important feature of a given center that is likely to have a large impact on the degree to which diversification will affect routines. The problem with measuring patient composition will be the inverse of the issue with the extent of actual diversification—although patient risk factors and complexity are easily measurable, a lack of theoretical exploration of this feature will make forming a cogent hypothesis difficult. This is largely a function of the lack of extensive work in a health care setting. The composition of inputs is largely ignored in the focused factory literature in manufacturing, while the dearth of longitudinal studies in a health care setting prevents this question from being raised. It will be important to test whether diversification has a differential impact on any given patient population in order to understand whether focus is preferable for all patients and all firms. It may be that more complex patients suffer disproportionately from the distraction of effort; while it is not possible to form a hypothesis in the absence of *a priori* explanations, I hope to help advance the literature in this area by presenting these preliminary findings.

Extension 2: diversification will have a detrimental effect on patient outcomes in complicated cases.

One of the key features in the mechanism that distinguishes the focused factory and related diversification literatures is repetition: that the primary goal of focus is to allow the development of routines that can be repeated, and that through this repetition workers' efficacy will be improved. If this is indeed the mechanism at work in the transplant center setting, then one would expect that the detrimental effect of diversification would decline with repetition. That is, as employees of diversified centers are able to develop and repeat new routines to accommodate for multiple tasks, any effect of diversification should decline:

Extension 3: diversification will have a detrimental effect on patient outcomes that declines over time.

The degree of repetition should also interact with the size of the firm. The size metric alone has already been discussed as a potential boon to learning as well as a hindrance to efficiency and the creation of coordination difficulties. Thus, in order to understand better how the volume of procedures within a center may enable the development of routines, I will examine:

Extension 4: diversification will have a detrimental effect on patient outcomes in centers where the volume of procedures is low and the share of the focal procedure is high.

Finally, it will be necessary to ensure that the hypotheses described above will be robust to the empirical issues that plague the estimation of diversification. The primary issue that needs to be addressed in such a setting is selection. In the case of transplant centers, firms can influence their risk-adjusted mortality rates in two ways. The first is through firm selection; while this setting differs from the diversification discount literature in terms of the mechanism, it faces the same selection problem in that diversification is not randomly assigned among firms, but rather selected as a firm strategy. To the extent that diversified and undiversified firms differ systematically in characteristics that would affect mortality, this will create a selection bias in results. One might assume that, if anything, this should lead to underestimating the effect of diversification, since it seems logical that firms that select into diversification would be those that would benefit from it. As demonstrated in the diversification discount literature, notably Villalonga (2004), selection into diversification may in fact lead to the overestimation of a negative effect of diversification. Thus it will be necessary to ensure that any results are not altered by selection.

While firm selection is a well-established phenomenon, the possibility for input selection is not typically addressed. In this particular setting, it will be necessary to understand the effect of a change in patient characteristics as a result of diversification versus focus. Although there is no established theory to predict this, a number of claims have been made regarding the relationship between diversification and patient mix. Some allege that high-profile centers will attract patients who are better able to travel, and therefore less sick (Huckman and Zinner, 2008), while others maintain that more prestigious programs attract sicker patients who have greater incentive to travel (Capps et al, 2001). Still others maintain that hospitals (particularly specialty hospitals) are actively gaming the system, selecting only lower-risk patients and leaving diversified hospitals with a higher-risk patient population (Dranove, Kessler, McClellan, Satterthwaite, 2002; Devers et al, 2003). While it is unclear exactly which direction the effect will go, it is clear that it will be necessary to understand the impact of diversification on patient mix.

III. Setting and Sample

Market characteristics: the nationwide Organ Procurement and Transplantation Network (OPTN) was created in 1986 and oversees the allocation of transplants. The service is provided by the United Network for Organ Sharing (UNOS), which is a nonprofit voluntary organization; participation in UNOS by transplant centers is not mandatory, although all US transplant programs have complied with UNOS policies voluntarily.

Each transplant center receives organs for transplant from a geographically designated Organ Procurement Organization (OPO), which is independent from the hospitals it supplies. Although OPOs are defined geographically, they do not conform to any particular geographic boundary—in less populous areas there may be multiple states served by a single OPO, whereas more populous states may have multiple OPOs. Beginning January 1, 1996, the Health Care Financing Administration required that an OPO include an entire state or territory, or that it recover organs from at least 50 potential or 24 actual donors per calendar year. While a small portion of organs may be transferred from one OPO to another, each transplant center receives all its organs from its designated OPO. Although in theory organs may be shared nationwide in order to maximize social welfare, inter-OPO transplant supply sharing beyond the 12 geographic regions (designated by groups of states) is uncommon.

Kidneys are allocated to different centers within an OPO to minimize the amount of mismatch between the recipient and the donor—first on HLA antigens, then blood type, etc. Waitlisted patients are ranked by a computer algorithm that assigns points to various relevant characteristics: time on waitlist, quality of the match, child or not, unavailability of the patient, etc. There are minimum acuity requirements to be placed on the waitlist, presumably to prevent patients from "gaming the system" as in the liver allocation market (Snyder, 2010). The allocation of kidneys (unlike livers) takes into account only fairness and match quality, and not the severity of the illness; currently, time on the waiting list receives the most weight in allocation decisions (OPTN Kidney Allocation Concepts for Public Comment). Some OPOs have exceptions for patients with demonstrated "urgent need" but the majority does not.

Firm Characteristics: There are a total of 293 kidney centers observed in the data, of which 244 were still performing transplants in 2007; of these, 150 also performed liver transplants. Among the transplant centers observed in the sample, only 2 (out of 150) centers that performed liver transplants did not also perform kidney transplants; thus, generally speaking, the pool of transplant centers that perform kidney transplants can be viewed as the set of potential entrants to the liver market. Transplant centers can operate between one and eight transplant programs. Almost all transplant centers (243 of 255 in 2010) perform kidney transplants, while fewer centers have other programs. In order to be eligible to receive Medicare reimbursement for kidney transplants, centers must perform a minimum of 15 transplants per year; however, it is possible for firms to reach this minimum volume in the accreditation year, and then fall back below subsequently.

When a center decides to expand into livers, the start-up costs are non-trivial: nursing coordinators must be trained differently for different transplants, and centers often hire a separate transplant surgeon for liver transplants. Furthermore, there are volume concerns to be addressed: in a new program, there may not be sufficient volume to support the income of two surgeons. Kidney transplant surgeons may work in general surgery to make up income (e.g., urology), while liver transplant surgeons will typically do other types of liver surgeries.

Demand characteristics:

For kidneys, a patient contacts a transplant center (or more than one transplant center) for evaluation (some transplant centers require the referring physician to contact the center, others allow the patient to refer himself); if deemed suitable for a transplant, he or she will be placed on that center's waitlist. A patient may apply before he or she begins dialysis, but are not considered officially "on the waitlist" until certain clinical thresholds are met.[7] In the case of both livers and kidneys, patients may also obtain an organ (for kidneys) or a part of an organ (for livers) from a live donor. While less than 5 percent of liver donations come from living donors, 32 percent of kidney donations are from living donors.

When a kidney becomes available, it will first be offered to the preferred patient within that OPO; if no suitable patient is on the waitlist in that OPO, it will be offered to the preferred patient in that OPO's region. The supply and demand for organs varies significantly by region, so wealthy patients who are able to travel will often enter waitlists in OPOs with lower wait times. The median wait time for kidneys in 2001 (most recent available for all states) nationwide was 3.23 years (1180 days); in California, the median wait was 6.41 years (2342 days), while in Oregon it was only 9 months (275 days) (UNOS 2009 Annual Report).

[7] Glomerular filtration rate drops to 0.20 mL per minute or lower

Sample Selection: The analysis presented here deals with liver and kidney transplants performed by United States transplant centers in the years 1988 to 2007. The data provided by UNOS is not a sample, but rather the universe of patients in the United States who were ever registered on a waitlist or received a transplant, and provides the clinical details of every patient and transplanted organ in that time period. In order to isolate the impact of diversification, I simplify the setting as much as possible: waitlisted patients who do not receive transplants are omitted, as are multi-organ transplants (such as a simultaneous kidney and pancreas transplant, for example). I also omit observations for which the transplant center performed less than the minimum volume to be eligible for Medicare (15 kidney transplants).[8] Liver data were aggregated to the center level and were merged into the kidney transplant data, using the unique center identification codes provided by UNOS. The resultant data comprises the universe of kidney transplants at centers that are or would be federally accredited between 1988 and 2007.

IV. EMPIRICAL STRATEGY

In order to test the impact of focus on performance, the dependent variables for all hypotheses will be patient mortality within a year, as this is consistent with clinical literature, and is the metric which UNOS publishes for all centers and transplants. I define a center as being diversified at the time of transplant if that center has done liver transplants in years prior to and including the year in which the transplant was performed. Given technological advances in surgical techniques, mortality has been steadily declining over time [FIGURE 1 & 2], thus all specifications will include transplant-year fixed effects. Similarly, in order to

[8] These centers may still be eligible for Medicare reimbursement. A center need only meet the minimum volume threshold in accreditation years. While centers may be re-evaluated after the initial accreditation, it does not (usually) happen annually. Thus, this exclusion omits centers that would not have been accredited in a given year, had they been evaluated.

isolate the effect of diversification in general and avoid reflecting any inherent center-level quality selection, I also include center-level fixed effects in all specifications.

Consistent with previous literature, I will use the number of procedures performed to control for firm learning. Recent experience has been shown to be a strong predictor of learning (Ramanarayanan, 2008), and traditionally the previous year's volume is used. Given the volatility in the transplant industry due to supply shocks, I will expand this to kidney transplant volume in the 3 years prior to transplant to control for recent firm learning. Since firms may vary hugely on this metric (see Table 2), using dummy variables for the volume quartile will allow for both easier interpretation and non-linear trends. Transplant volumes may also affect outcomes through the quality of donor transplants. Some hospital executives have noted that when volumes are low and the supply of transplantable organs is volatile, some centers may accept transplants of below-average quality. Thus I will also include controls for market concentration and kidney supply.[9] Concentration is calculated as the Herfindahl index for kidney transplants for centers within a given OPO. Based on the structure of the OPO market, and the fact that demand is strictly greater than supply, I use the total number of kidney transplants in a region as a proxy for the supply of organs.

Finally, I include clinical controls to adjust for idiosyncratic patient risk. When publishing risk adjusted mortality rates, UNOS controls only for race, sex, age and primary kidney diagnosis. I also include non-UNOS risk-adjustment measures common in other risk adjustment methodologies that have demonstrated success in predicting outcomes: B-antigen mismatch level, DR-antigen mismatch level, the number of previous kidney transplants, and whether the kidney came from a live donor.

[9] Specifications including a measure of the quarterly volatility of transplant supply are omitted. The effect was miniscule and insignificant, and its inclusion or omission had no impact on the other coefficients of interest.

The baseline specification for patient *i* at center *c* in year *t* (in OPO *o* and Region *r*) is:

$$
\begin{aligned}
Outcome_{ictor} = \ & \beta_0 + \ \beta_1 Diversified_{ctor} + \beta_2 Volume\ Quartile_{ctor} \\
& + \beta_3 Concentration_{tor} \ + \beta_4 Supply_{rt} + \ Year_t + \ Center_c \\
& + Patient\ Controls_i + \varepsilon_{ictor}
\end{aligned}
$$

For Extension 2 I will expand this specification to allow for the possibility of interactions between diversification and the patient control variables that have a demonstrable impact on outcomes. Extension 3 will replace the diversification indicator variable with two alternative measures of time since diversification: as a continuous variable, and also as a dummy for more or less than five years since diversification. The specification latter will allow for non-linearity in the time trend, while still facilitating interpretation of the results. Finally, Extension 4 will return to the baseline specification of diversification, and include a measure of focus: the natural log of the ratio of a given center *c*'s kidney transplants to that center's total kidney and liver transplants in the past three years.

The impact of focus on mortality is a particularly thorny issue to address empirically because mortality may be endogenous to the diversification decision. To a certain extent, selection will be addressed by the inclusion of firm-specific fixed effects. There will continue to be a problem, however, if some idiosyncratic firm characteristic that varies over time influences both the diversification decision as well as patient outcomes. If unobservable factors that motivate diversification are time invariant, then the center fixed effects will be sufficient. The question is whether factors that influence diversification that may also influence outcomes are varying over time. As shown in Figure 4, among centers that diversified in the sample, there does seem to be the possibility of time-varying selection in graft mortality rates, although the effect is not strong, and may be due to overall declines in mortality rates. Thus, the findings of Hypothesis 1 will need to be robust to such additional selection controls.

Propensity score matching is typically used to deal with selection on observables problems; however, the definition of the before and after treatment periods is virtually impossible for untreated variables, since treatment occurs for each center at a different time. For this reason, as a robustness check it will be better to rely on the inverse-probability weight treatment, which allows for time variation. I will follow the methodology of Azoulay (2006); see his paper for an exhaustive explanation of this methodology. In short, I will use a probit model to estimate the probability that a given center will be diversified in a given year, based on characteristics of both the firm and its market:

$$\begin{aligned}\Pr(Diversified_{ctor} = 1) \\ &= \beta_0 + \beta_1 Volatility_{ctor} + \beta_2 Volume_{ctor} + \beta_3 Liver\ Centers_{or,t-1} \\ &+ \beta_4 Concentration_{tor} + \varepsilon_{ctor}\end{aligned}$$

Each observation is assigned a weight equal to the inverse of the probability that the center will be diversified in that year. The results of this specification are included in Appendix A of the results.

As a final robustness check, it will be necessary to test the relationship between patient characteristics and diversification of centers to determine if results could be affected by strategic patient selection. If focused or diversified centers have significantly different patient populations than their counterparts due to selection, we would expect that diversification should be a significant predictor of patient characteristics. It will also be necessary, however, to control for other aspects of the center and market that may also influence patient mix. I will include three year center kidney volume and regional kidney supply as controls—diversity of the patient population should be simply mechanically related to the size of the population served by a center. The specification should also include year fixed effects to account for population changes (e.g., the increase in the Hispanic population), as well as center fixed effects to account for time-invariant, center-level heterogeneity. For instance, it may be that diversified centers are more common in large, urban areas, so the relevant patient population is more racially diverse for all years.

V. RESULTS

Summary Statistics

Table 1 summarizes the key patient variables used to measure patient outcomes. On a non-risk-adjusted basis, patient mortality does not differ much on average between diversified centers and the population overall. Table 2 presents a summary of all transplant centers, while tables 3 and 4 illustrate the superficial differences between diversified and undiversified centers. Diversified centers are "larger" than undiversified centers on virtually every dimension: larger annual transplant volumes (79.6 versus 56.2), cumulative volumes (769.8 versus 502.5), and regional supply of transplantable organs (1497.2 versus 660.4). In terms of competition, however, diversified and undiversified centers are more similar. Both face similarly competitive markets in terms of other centers in the OPO and the market concentration (measured using a Herfindahl index for kidney transplants). Unsurprisingly, diversified centers also tend to be older, with 10.4 years of experience versus 7.3 for undiversified firms. One might reasonably expect that these differences are more "mechanical" than causal, and simply reflect the dynamics of the market: nearly all transplant centers perform kidney transplants, and may later add additional transplant programs. Thus it is completely natural for diversified kidney programs to be older, larger, and have a larger scope. Regardless of the reason, these statistics do highlight the importance of controlling for the center characteristics that may impact performance.

The basic results are presented in Table 5. Model 1 demonstrates the main effect of diversification when other center- and market-level characteristics are not controlled for—the results are quite small and not at all significant. The inclusion of market concentration (Model 2) appears to have very little effect on the magnitude of the coefficient on diversification. The inclusion of an effect for the size of the center alone for Extension 1 (Model 3) has an impact on the main effect, but the findings for each of the volume quartiles are not significant.[10] Readers who are familiar with the learning-by-doing literature in health care may nonetheless be surprised by these results—although not significant, they suggest that large and medium volume centers have higher mortality rates (or at the minimum, no better) than the baseline low-volume center. This appears to contradict the wide body of learning-by-doing literature that has demonstrated that mortality rates decrease with volume of procedures discussed earlier. To ensure comparability with this literature, I also tested the risk-adjusted specification of a clinical study that used five years of data from the same UNOS data-set employed here (Axelrod et al, 2003). In these specifications, volume does reduce mortality rates across centers. When a center-specific fixed effect is included[11], however, the impact of volume becomes small and positive, although not significant. This result is consistent with

[10] The number of observations is lower in specifications that include volume effects—observations in 1988 and 1989, for which 3 year volume cannot be calculated, are excluded from these specifications.

[11] Center fixed effects are not included in the specifications of Axelrod et al (2003).

Gjertson (2002), which demonstrated that while center-effects significantly predicted kidney re-graft outcomes, transplant center volume was not significant.

In contrast with the insignificance of center volume effects, in Model 4 the inclusion of an interaction between the size of the center and diversification increases the magnitude of the main effect substantially, from 0.6% to 1.8%. The inclusion of controls for kidney supply in Model 5 mitigates this somewhat, but does not significantly alter this coefficient. Controlling for overall time trends, center-specific heterogeneity, and patient risk factors, diversification in the smallest centers increases patient mortality by 1.7% (compared with an unconditional mean of 4.6%), significant at the 90% level. In absolute terms, 1.7% translates to approximately 229 patient deaths per year. It is interesting to note that centers with volumes in the 25th-50th percentile (Low Volume Centers) have higher mortality rates overall, but this differential is almost entirely offset if they are also diversified. While the interaction between center size and diversification is negative for all firms above the bottom quartile, the results are only significant at the 90% level for low volume centers.

Table 6 tests the robustness of these results through inverse-probability weighting; while the coefficients in Model 5 are largely unaffected, the impact of diversification for centers above the lowest quartile of volume are no longer significant.[12] The impact of diversification for the lowest quartile, however, is still large—an increase in mortality rates of 1.8% relative to undiversified centers, still significant at the 90% level. The fact that this coefficient differs only very slightly with the inclusion of inverse probability weights suggests that selection into diversification (beyond individual firm effects) does not significantly affect

[12] The number of observations is lower for all specifications that include inverse probability weighting. Probability weights cannot be constructed for observations that do not record the variables used to predict entry; only observations for which all explanatory variables and predictive variables were recorded are used.

mortality rates. Also, since the inclusion of probability weights tends to very slightly increase the coefficient on diversification, it suggests that if anything center selection leads to slight underestimates of diversification. These results are not significantly different, however, and so we can really only say that the detrimental impact of diversification is robust to multiple corrections for selection.

Tables 7 through 10 attempt to shed further light on the mechanism by which diversification may impact center mortality rates. Tables 7 and 8 addresses Extension 2, the possibility that diversification may be a superior strategy for more complicated patients. The results are mixed: for two out of four factors that increase the difficulty of a case (B-antigen mismatch and previous kidney transplants), the results are not significant. The other two factors do interact with diversification in a significant way, but in opposite directions. In Model 2, age significantly reduces the risk of mortality at diversified firms. While this effect is extremely small (-0.0268% with selection correction, significant at the 99% level), this can result in large changes over the span of ages. For a 20 year old patient and a 60 year old patient, the 60 year old will have an expected mortality rate that is 1.1% lower than the 20 year old at a diversified center. [13] Given the magnitude of the coefficient on diversification, it is unlikely that even the oldest patients will offset the deleterious effect of diversification entirely, although it will likely be significantly reduced. For a center that treats a disproportionate share of older patients, diversification may not be as detrimental to the center's mortality performance. On the other hand, DR-Antigen mismatch is demonstrably worse for survival at a diversified rather than undiversified center—an increase in mortality rates of 0.3% which is largely unaffected by selection correction (although significance drops

[13] On a relative basis. Naturally a 60 year old will have a higher mortality rate than a 20 year old, all else equal.

from 95% to 90%). While the exact mechanism by which diversification may interact with these measures of complexity cannot be identified here, this certainly suggests that the degree to which diversification will affect a firm will vary with both center and patient characteristics.

Table 9 presents results from Extension 3, the impact of diversification on firm outcomes over time. These results are perhaps the most surprising, and thereby potentially the most informative: the increase in mortality rates associated with diversification increases over time. The "baseline" scenario presented here gives the effect of diversification overall, without the interactions between firm size or patient characteristics. When the time since diversification is included in the specification, whether as a continuous variable (Model 1) or as a dummy for more or less than five years since diversification, greater time results in greater risk. That is, the effect of diversification does not dissipate, but rather becomes exacerbated over time. Once again, this effect differs across centers by the size of their operations. In Model 3, where time since diversification is interacted with center size, we see that this effect is even more pronounced for the smallest centers while it is significantly ameliorated (although again, not completely offset) for firms above the lowest quartile of volumes. Finally, Table 10 allows for some variability in the degree of diversification; in addition to the binary diversified-or-not measure, I examine the percentage of transplants in the previous three years that were kidneys and not livers as a measure of focus within a diversified center to address Extension 4. This measure is not a significant predictor of mortality in any of these specifications, whether as a main effect or when interacted with firm size.

VI. Conclusions

The results presented in this paper support the hypothesis that diversification will have a detrimental impact for some centers, and less so for others. Yet, given the relatively muted effect of firm selection into the strategy of diversification in each of the extensions, it seems that centers are either unaware of these detrimental effects, or that diversification may serve another goal that is unobservable here. Regardless, the social and strategic implications of diversification for mortality necessitate discussion in the health policy realm regarding whether the potentially unobserved benefits of diversification outweigh these effects.

For the strategy literature more generally, these results can help clarify the mechanisms by which focus may improve performance, and call attention to the importance of how we define relatedness. While these results support process-focus in the health care industry, the variation in the response for patient characteristics—that older patients will not suffer at a diversified center, whereas patients with a poorer organ match will suffer more—lends important support to the idea of defining relatedness or focus at a process level. For firms in these industries, the lines between service and manufacturing are blurred; while process focus makes natural sense in a manufacturing setting, one might not think of it in a service setting. These results demonstrate crucially that the degree of relatedness businesses is not only defined by the industry, but by its inputs. In industries such as health care and education, where a malfunctioning input cannot simply be discarded or ignored, focus at the input level may have large strategic consequences.

While these findings provide preliminary evidence to advance the study of process focus in non-manufacturing industries, the primary limitation of these findings is the absence of comparably precisely-measured characteristics of the centers as well as patients. It appears that the negative impact of diversification is substantially mitigated for larger firms, but firm size is correlated with too much unobserved heterogeneity in firm characteristics to precisely measure or interpret this effect. In particular, future research would do well to examine a more precise measure of diversification, one that allows for a diversified firm that is able to maintain its operating units separately.

In order for health care providers to reap the potential benefits of factory focus, it is important to know how exactly a particular firm may or may be able to benefit from this strategy. This paper has demonstrated how firms that serve particular patient populations may benefit from a strategy of focus versus related diversification, as well as indicated the fruitfulness of understanding the importance of firm characteristics. Despite its limitations, these findings contribute to the growing body of research that seeks to explicate the importance of focus in health care.

TABLES

Table 1: Patient Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Patient mortality	271,179	0.046	0.210	0	1
Diversified centers patient mortality	169,908	0.045	0.206	0	1
Focused centers patient mortality	101,271	0.049	0.216	0	1
White	271,179	0.620	0.485	0	1
Black	271,179	0.216	0.411	0	1
Asian	271,179	0.036	0.185	0	1
Hispanic	271,179	0.116	0.320	0	1
Other race	236,224	-	-	0	0
Age	271,179	43.713	15.092	0	90
Days on Waiting list	271,179	425.118	538.546	0	7915
B antigen mismatch level	269,081	1.217	0.737	0	2
DR antigen mismatch level	267,979	0.981	0.722	0	2
Number of previous kidney transplants	271,178	0.095	0.315	0	5
Live Donors	271,179	0.320	0.466	0	1

Table 2: Center Descriptive Statistics- all

Variable	Obs	Mean	Std. Dev.	Min	Max
Diversified	4,824	0.444	0.497	-	1
3 year kidney volume	3,924	170.606	170.549	-	1,340
Cumulative kidney volume	4,824	502.528	674.166	-	5,765
OPO Concentration	4,824	0.354	0.225	-	1
Annual kidney transplant volume	4,824	56.215	58.545	-	486
Count of centers in OPO	4,824	6.316	3.606	1	15
Regional Kidney supply	4,824	1,416.367	660.366	304	3,023
Quarterly kidney volatility (annual average)	4,779	2.933	2.263	-	19.820
Unique 2-digit ZIP codes served	4,702	4.451	4.813	1	57

Table 3: Center Descriptive Statistics, Diversified

Variable	Obs	Mean	Std. Dev.	Min	Max
Annual kidney transplant volume	2143	79.59403	73.70434	0	486
3 year kidney volume	1973	227.4247	209.8259	0	1340
Cumulative kidney volume	2143	769.8483	869.4274	0	5765
Count of centers in OPO	2143	6.117337	3.718502	1	15
OPO Concentration	2143	0.3782241	0.25084	0.091674	1
Regional Kidney supply	2143	1497.19	683.0801	344	3023
Quarterly kidney volatility (annual average)	2134	3.603688	2.704224	0	19.81965
Unique 2-digit ZIP codes served	2084	6.274472	6.395547	1	57
Years experience in kidney transplants	2143	10.41997	5.352645	0	19

Table 4: Center Descriptive Statistics, Undiversified

Variable	Obs	Mean	Std. Dev.	Min	Max
Annual kidney transplant volume	4824	56.21455	58.54483	0	486
3 year kidney volume	3924	170.6055	170.5491	0	1340
Cumulative kidney volume	4824	502.528	674.1656	0	5765
Count of centers in OPO	4824	6.3156	3.605868	1	15
OPO Concentration	4824	0.354109	0.225086	0	1
Regional Kidney supply	1416.367	660.3659	304	3023	
Quarterly kidney volatility (annual average)	4779	2.933092	2.26305	0	19.81965
Unique 2-digit ZIP codes served	4702	4.450872	4.812948	1	57
Years experience in kidney transplants	2681	7.271167	5.626293	0	19

Table 5: Impact of Diversification on Patient Mortality, Unweighted

Dependent variable: patient mortality within 1 year

	Model 1	Model 2	Model 3	Model 4	Model 5
Diversified	0.002	0.002	0.006*	0.018*	0.017*
	(0.003)	(0.003)	(0.003)	(0.010)	(0.009)
Market concentration		0.004	0.000	0.001	0.002
		(0.008)	(0.010)	(0.010)	(0.010)
Low Volume Center§			0.006	0.011**	0.011**
			(0.004)	(0.005)	(0.005)
Med Volume Center			0.007	0.010*	0.011*
			(0.005)	(0.006)	(0.006)
Highest Volume Center			0.004	0.009	0.009
			(0.005)	(0.006)	(0.006)
Low Volume Center * Diversify				-0.015*	-0.015*
				(0.009)	(0.009)
Med Volume Center * Diversify				-0.010	-0.010
				(0.010)	(0.010)
Highest Volume Center * Diversify				-0.014	-0.013
				(0.010)	(0.010)
Regional kidney supply					0.000**
					(0.000)
Constant	0.022***	0.020***	0.001	-0.004	-0.019*
	(0.005)	(0.007)	(0.008)	(0.009)	(0.010)
R^2	0.026	0.026	0.025	0.025	0.025
N	247,180	247,180	219,961	219,961	219,961
Time and Center Fixed Effects	Yes	Yes	Yes	Yes	Yes
Patient risk adjustment	Yes	Yes	Yes	Yes	Yes

* p<.10, ** p<.05, *** p<.01

§ As defined by center 3 year transplant volume quartile. The lowest quartile centers are omitted category

Standard errors are robust and clustered by transplant center

Table 7: Impact of Diversification and Patient Characteristics on Patient Mortality, Unweighted

Dependent variable: patient mortality within 1 year

	Model 1	Model 2	Model 3	Model 4	Model 5
Diversified	0.017* (0.009)	0.015 (0.010)	0.017* (0.009)	0.025** (0.010)	0.015 (0.010)
Market concentration	0.002 (0.010)	0.002 (0.010)	0.002 (0.010)	0.002 (0.010)	0.002 (0.010)
Low Volume Center§	0.011** (0.005)	0.011** (0.005)	0.011** (0.005)	0.011** (0.005)	0.011** (0.005)
Med Volume Center	0.011* (0.006)	0.011* (0.006)	0.011* (0.006)	0.010* (0.006)	0.011* (0.006)
Highest Volume Center	0.009 (0.006)	0.010 (0.006)	0.009 (0.006)	0.009 (0.006)	0.010* (0.006)
Low Volume Center * Diversify	-0.015* (0.009)	-0.016* (0.009)	-0.015* (0.009)	-0.015* (0.009)	-0.016* (0.009)
Med Volume Center * Diversify	-0.010 (0.010)	-0.010 (0.010)	-0.010 (0.010)	-0.009 (0.010)	-0.011 (0.010)
Highest Volume Center * Diversify	-0.013 (0.010)	-0.014 (0.010)	-0.014 (0.010)	-0.012 (0.010)	-0.014 (0.010)
Regional kidney supply	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)
B-Antigen Mismatch * Diversified		0.002 (0.001)			
Previous Kidney Transplant * Diversified			0.005 (0.004)		
Age * Diversified				-0.000* 0.000	
DR-Antigen Mismatch * Diversified					0.003** (0.001)
Constant	-0.019* (0.010)	-0.018* (0.010)	-0.019* (0.010)	-0.025** (0.010)	-0.017* (0.010)
R^2	0.025	0.025	0.025	0.025	0.025
N	219,961	219,961	219,961	219,961	219,961
Time and Center Fixed Effects	Yes	Yes	Yes	Yes	Yes
Patient risk adjustment	Yes	Yes	Yes	Yes	Yes

* p<.10, ** p<.05, *** p<.01

§ As defined by center 3 year transplant volume quartile. The lowest quartile centers are omitted category

Standard errors are robust and clustered by transplant center

Table 8: Impact of Diversification and Patient Characteristics on Patient Mortality, Weighted

Dependent variable: patient mortality within 1 year

	Model 1	Model 2	Model 3	Model 4	Model 5
Diversified	0.018*	0.018*	0.018*	0.029***	0.016
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)
Market concentration	0.001	0.001	0.001	0.001	0.001
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Low Volume Center§	0.012**	0.012**	0.012**	0.011**	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Med Volume Center	0.012*	0.012*	0.012*	0.011*	0.012*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Highest Volume Center	0.01	0.01	0.01	0.009	0.010*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Low Volume Center * Diversify	-0.013	-0.013	-0.013	-0.013	-0.013
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Med Volume Center * Diversify	-0.011	-0.011	-0.011	-0.01	-0.011
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Highest Volume Center * Diversify	-0.013	-0.013	-0.013	-0.011	-0.014
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Regional kidney supply	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B-Antigen Mismatch * Diversified		0.001			
		(0.002)			
Previous Kidney Transplant * Diversified			0.004		
			(0.004)		
Age * Diversified				-0.000***	
				(0.000)	
DR-Antigen Mismatch * Diversified					0.003*
					(0.002)
Constant	-0.019*	-0.018*	-0.019*	-0.025**	-0.017
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
R^2	0.027	0.027	0.027	0.027	0.027
N	219,959	219,959	219,959	219,959	219,959
Time and Center Fixed Effects	Yes	Yes	Yes	Yes	Yes
Patient risk adjustment	Yes	Yes	Yes	Yes	Yes

* p<.10, ** p<.05, *** p<.01

§ As defined by center 3 year transplant volume quartile. The lowest quartile centers are omitted category

Standard errors are robust and clustered by transplant center

Table 9: Impact of Diversification Over Time on Patient Mortality

Dependent variable: patient mortality within 1 year

	Baseline	Baseline Weighted	Model 1 Unweighted	Model 1 Weighted	Model 2 Unweighted	Model 2 Weighted	Model 3 Unweighted	Model 3 Weighted
Diversified	0.005*	0.007**						
	(0.003)	(0.003)						
Years since diversification (continuous)			0.005**	0.006***				
			(0.002)	(0.002)				
Less than 5 years since diversification					0.005	0.006**	0.009	0.011
					(0.003)	(0.003)	(0.013)	(0.014)
5+ years since diversification					0.010**	0.012***	0.032***	0.035***
					(0.004)	(0.004)	(0.010)	(0.011)
Low volume * Less than 5 years							-0.005	-0.003
							(0.013)	(0.014)
Low volume * More than 5 years							-0.025**	-0.025**
							(0.010)	(0.011)
Medium volume * Less than 5 years							-0.002	-0.004
							(0.013)	(0.014)
Medium volume * More than 5 years							-0.021**	-0.022**
							(0.010)	(0.011)
Highest volume * Less than 5 years							-0.006	-0.007
							(0.014)	(0.014)
Highest volume * More than 5 years							-0.025**	-0.026**
							(0.010)	(0.011)
Market concentration	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.003
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
Low Volume Center§	0.006	0.008*	0.006	0.008*	0.006	0.008*	0.011**	0.012**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Med Volume Center	0.007	0.009*	0.007	0.009*	0.007	0.009*	0.011*	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Highest Volume Center	0.004	0.006	0.003	0.005	0.003	0.005	0.010*	0.011*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Regional kidney supply	0.000**	0.000	0.000**	0.000	0.000**	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.014	-0.015	-0.014	-0.015	-0.014	-0.015	-0.019**	-0.020*
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.011)
R^2	0.025	0.027	0.025	0.027	0.025	0.027	0.025	0.027
N	219,961	219,959	219,961	219,959	219,961	219,959	219,961	219,959
Time and Center Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient risk adjustment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* p<.10, ** p<.05, *** p<.01

§ As defined by center 3 year transplant volume quartile. The lowest quartile centers are omitted category

Standard errors are robust and clustered by transplant center

Table 10: Impact of Diversification and Focus on Patient Mortality

Dependent variable: patient mortality within 1 year

	Model 1 Unweighted	Model 1 Weighted	Model 2 Unweighted	Model 2 Weighted	Model 3 Unweighted	Model 3 Weighted
Diversified	0.004	0.007**	0.006*	0.007**	0.025*	0.025*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.013)	(0.014)
Log of Focus	0.006	0.004	0.003	0.002	0.013	0.010
(kidneys % of transplants)	(0.004)	(0.005)	(0.008)	(0.009)	(0.010)	(0.011)
Market concentration	-0.001	-0.001	0.000	0.000	0.001	0.000
	(0.009)	(0.011)	(0.010)	(0.012)	(0.010)	(0.012)
Regional kidney supply	0.000	0.000	0.000**	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Volume Center§			0.006	0.008*	0.011**	0.012**
			(0.005)	(0.005)	(0.005)	(0.005)
Med Volume Center			0.007	0.009*	0.011*	0.012*
			(0.005)	(0.005)	(0.006)	(0.006)
Highest Volume Center			0.004	0.006	0.009	0.010
			(0.006)	(0.006)	(0.006)	(0.006)
Low Volume Center * Log of Focus Share			0.002	0.003	-0.014	-0.01
			(0.010)	(0.010)	(0.014)	(0.015)
Med Volume Center * Log of Focus Share			0.001	0.002	-0.007	-0.006
			(0.009)	(0.009)	(0.011)	(0.012)
Highest Volume Center * Log of Focus Share			0.005	0.006	-0.006	-0.004
			(0.009)	(0.010)	(0.011)	(0.012)
Low Volume Center * Diversify					-0.025*	-0.021
					(0.013)	(0.015)
Med Volume Center * Diversify					-0.017	-0.017
					(0.014)	(0.015)
Highest Volume Center * Diversify					-0.020	-0.019
					(0.013)	(0.015)
Constant	0.022***	-0.007	-0.013	-0.014	-0.018*	-0.018
	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
R^2	0.026	0.026	0.025	0.027	0.025	0.027
N	235,101	219,959	219,961	219,959	219,961	219,959
Time and Center Fixed Effec	Yes	Yes	Yes	Yes	Yes	Yes
Patient risk adjustment	Yes	Yes	Yes	Yes	Yes	Yes

* p<.10, ** p<.05, *** p<.01

§ As defined by center 3 year transplant volume quartile. The lowest quartile centers are omitted category

Standard errors are robust and clustered by transplant center

Appendix A: Probit Model of Diversification Used to Generate Inverse Probability Weights

Dependent Variable: Transplant Center Diversification

	Model 1	Model 2	Model 3	Model 4
Center Quarterly Transplant Volatility	-0.170*** (0.009)	-0.086*** (0.013)	-0.087*** (0.013)	-0.056*** (0.015)
Lowest Volume Center§		0.667*** (0.076)	0.688*** (0.077)	0.398*** (0.097)
Low Volume Center		1.342*** (0.069)	1.360*** (0.070)	1.053*** (0.087)
Med Volume Center		0.649*** (0.063)	0.658*** (0.064)	0.369*** (0.075)
Liver Centers in OPO in previous year			-0.119*** (0.011)	-0.218*** (0.014)
Kidney market concentration				-1.642*** (0.139)
Constant	0.545*** (0.032)	-0.461*** (0.076)	-0.113 (0.083)	1.027*** (0.127)
N	4,779	3,903	3,903	3,903
				IPW based on this model

* p<.10, ** p<.05, *** p<.01

§ As defined by center 3 year transplant volume quartile. The lowest quartile centers are omitted category

Standard errors are robust and clustered by transplant center

Appendix B: Patient Characteristics as Dependent Variables

Dependent variable: patient mortality within 1 year

Patient Characteristic	Year Fixed Effects	Center Fixed Effects	Diversified	(SE)	R^2	N
White	No	No	-0.012***	(0.002)	0.016	239,288
White	Yes	No	-0.011	(0.007)	0.017	239,288
White	Yes	Yes	-0.014	(0.012)	0.159	239,288
Black	No	No	0.021***	(0.002)	0.006	239,288
Black	Yes	No	0.021***	(0.003)	0.006	239,288
Black	Yes	Yes	-0.003	(0.009)	0.140	239,288
Asian	No	No	0.000	(0.001)	0.002	239,288
Asian	Yes	No	0.000	(0.001)	0.002	239,288
Asian	Yes	Yes	0.000	(0.004)	0.061	239,288
Hispanic	No	No	-0.008***	(0.002)	0.006	239,288
Hispanic	Yes	No	-0.009*	(0.005)	0.007	239,288
Hispanic	Yes	Yes	0.016	(0.012)	0.215	239,288
Age	No	No	-1.950***	(0.073)	0.011	239,288
Age	Yes	No	-2.177***	(0.084)	0.032	239,288
Age	Yes	Yes	0.453	(0.311)	0.141	239,288
B Mismatch	No	No	0.051***	(0.004)	0.005	237,534
B Mismatch	Yes	No	0.049***	(0.006)	0.021	237,534
B Mismatch	Yes	Yes	0.037	(0.024)	0.042	237,534
DR Mismatch	No	No	0.050***	(0.004)	0.004	237,049
DR Mismatch	Yes	No	0.045***	(0.006)	0.016	237,049
DR Mismatch	Yes	Yes	0.024	(0.020)	0.034	237,049
Previous Kid Transplants	No	No	0.006***	(0.002)	0.004	239,287
Previous Kid Transplants	Yes	No	0.004**	(0.002)	0.008	239,287
Previous Kid Transplants	Yes	Yes	-0.006	(0.006)	0.021	239,287
Live Donors	No	No	-0.011***	(0.002)	0.001	239,288
Live Donors	Yes	No	-0.017***	(0.005)	0.012	239,288
Live Donors	Yes	Yes	-0.011	(0.016)	0.061	239,288

* p<.10, ** p<.05, *** p<.01

§ As defined by center 3 year transplant volume quartile. The lowest quartile centers are omitted category

Standard errors are robust and clustered by transplant center

REFERENCES

Abecassis, M M. 2006. “Financial outcomes in transplantation--a provider’s perspective.” *American Journal of Transplantation: Official Journal of the American Society of Transplantation and the American Society of Transplant Surgeons* 6 (6) (June): 1257-1263. doi:10.1111/j.1600-6143.2006.01329.x.

Axelrod, David A, Mary K Guidinger, Keith P McCullough, Alan B Leichtman, Jeffrey D Punch, and Robert M Merion. 2004. “Association of Center Volume with Outcome After Liver and Kidney Transplantation.” *American Journal of Transplantation* 4 (6) (June 1): 920-927. doi:10.1111/j.1600-6143.2004.00462.x.

Azoulay, Pierre, Waverly Ding, and Toby Stuart. 2006. “The Impact of Academic Patenting on the Rate, Quality, and Direction of (Public) Research Output.” *National Bureau of Economic Research Working Paper Series* No. 11917 (January). http://www.nber.org/papers/w11917.

Capps, Cory S., David Dranove, Shane Greenstein, and Mark Satterthwaite. 2001. “The Silent Majority Fallacy of the Elzinga-Hogarty Criteria: A Critique and New Approach to Analyzing Hospital Mergers.” *National Bureau of Economic Research Working Paper Series* No. 8216 (April). http://www.nber.org/papers/w8216.

Chirikos, T N, and A M Sear. 2000. “Measuring hospital efficiency: a comparison of two approaches.” *Health Services Research* 34 (6) (February): 1389-1408.

Choti, M. 1998. “Should hepatic resections be performed at high-volume referral centers?” *Journal of Gastrointestinal Surgery* 2 (1) (February): 11-20. doi:10.1016/S1091-255X(98)80098-X.

Clark, Jonathan, and Robert S. Huckman. 2011. “Broadening Focus: Spillovers, Complementarities and Specialization in the Hospital Industry.” *SSRN eLibrary* (April 30). http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1375020.

Coburn, David, Carl D’Arcy, and George Murray Torrance. 1998. *Health and Canadian society: sociological perspectives*. University of Toronto Press, August 15.

Devers, Kelly J, Linda R Brewster, and Paul B Ginsburg. 2003. “Specialty hospitals: focused factories or cream skimmers?” *Issue Brief (Center for Studying Health System Change)* (62) (April): 1-4.

Dranove, David, Daniel Kessler, Mark McClellan, and Mark Satterthwaite. 2002. “Is More Information Better? The Effects of ‘Report Cards’ on Health Care Providers.” *National Bureau of Economic Research Working Paper Series* No. 8697 (January). http://www.nber.org/papers/w8697.

Edmondson, Amy C., Richard M. Bohmer, and Gary P. Pisano. 2001. “Disrupted Routines: Team Learning and New Technology Implementation in Hospitals.” *Administrative Science Quarterly* 46 (4) (December 1): 685-716. doi:10.2307/3094828.

Gjertson, David W. 2002. “A multi-factor analysis of kidney regraft outcomes.” *Clinical Transplants*: 335-349.

Hayes, Robert H., and Gary P. Pisano. 1996. “Manufacturing Strategy: at the Intersection of Two Paradigm Shifts.” *Production and Operations Management* 5 (1) (March): 25-41.

Huckman, Robert S., and Darren E. Zinner. 2008. “Does focus improve operational performance? Lessons from the management of clinical trials.” *Strategic Management Journal* 29 (2) (February): 173-193. doi:10.1002/smj.650.

Hyer, Nancy Lea, Urban Wemmerlöv, and John A. Morris Jr. 2009. “Performance analysis of a focused hospital unit: The case of an integrated trauma center.” *Journal of Operations Management* 27 (3) (June): 203-219. doi:10.1016/j.jom.2008.08.003.

Inman, Robert R, Dennis E Blumenfeld, and Arthur Ko. 2005. “Cross-training hospital nurses to reduce staffing costs.” *Health Care Management Review* 30 (2) (June): 116-125.

Kraus, Thomas W., Markus W. Büchler, and Christian Herfarth. 2005. Relationships between Volume, Efficiency, and Quality in Surgery — A Delicate Balance from Managerial Perspectives. *World Journal of Surgery* 29 (10): 1234-1240. doi:10.1007/s00268-005-7988-5.

Levine, Susan. 2006. Organ Transplant Centers Face Federal Scrutiny. *Transplant Connect*. October 6. http://www.transplantconnect.com/news_detail.php?id=25.

Luft, H S, J P Bunker, and A C Enthoven. 1979. “Should operations be regionalized? The empirical relation between surgical volume and mortality.” *The New England Journal of Medicine* 301 (25) (December 20): 1364-1369. doi:10.1056/NEJM197912203012503.

Mazzola, Joseph B., and Robert H. Schantz. 1995. “Single-Facility Resource Allocation under Capacity-Based Economies and Diseconomies of Scope.” *Management Science* 41 (4) (April 1): 669-689.

Mukherjee, Ashok, Will Mitchell, and F. Brian Talbot. 2000. “The impact of new manufacturing requirements on production line productivity and quality at a focused factory.” *Journal of Operations Management* 18 (2) (February): 139-168. doi:16/S0272-6963(99)00023-6.

Ozcan, Yasar A., Roice D. Luke, and Cengiz Haksever. 1992. “Ownership and Organizational Performance: A Comparison of Technical Efficiency across Hospital Types.” *Medical Care* 30 (9): 781-794.

Organ Procurement and Transplantation Network. 2011. Concepts for Kidney Allocation. (February 16, 2011) doi: http://optn.transplant.hrsa.gov/SharedContentDocuments/KidneyConceptDocument.PDF

Palepu, Krishna. 1985. "Diversification Strategy, Profit Performance and the Entropy Measure." *Strategic Management Journal* 6 (3): 239-255.

Panzar, John C, and Robert D Willig. 1981. "Economies of Scope." *American Economic Review* 71 (2). American Economic Review: 268-72.

Porter, Michael E, and Elizabeth Olmsted Teisberg. 2004. "Redefining competition in health care." *Harvard Business Review* 82 (6) (June): 64-76, 136.

Ramanarayanan, Subbu. 2008. "Does Practice Make Perfect: An Empirical Analysis of Learning-by-Doing in Cardiac Surgery." *SSRN eLibrary* (April). http://papers.ssrn.com/Sol3/papers.cfm?abstract_id=1129350.

Rodriguez, Hector P., Ira B. Wilson, Bruce E. Landon, Peter V. Marsden, and Paul D. Cleary. 2007. "Voluntary Physician Switching by Human Immunodeficiency Virus-Infected Individuals." *Medical Care* 45 (3) (March): 189-198. doi:10.1097/01.mlr.0000250252.14148.7e.

Roth, Aleda V., and Larry J. Menor. 2009. "INSIGHTS INTO SERVICE OPERATIONS MANAGEMENT: A RESEARCH AGENDA." *Production and Operations Management* 12 (2) (January): 145-164. doi:10.1111/j.1937-5956.2003.tb00498.x.

Rumelt, Richard P. 1982. "Diversification Strategy and Profitability." *Strategic Management Journal* 3 (4): 359-369.

Shactman, David. 2005. "Specialty Hospitals, Ambulatory Surgery Centers, And General Hospitals: Charting A Wise Public Policy Course." *Health Affairs* 24 (3) (May 1): 868 -873. doi:10.1377/hlthaff.24.3.868.

Skinner, Wickham. 1974. The Focused Factory. *Harvard Business Review* 52, no. 3: 113-121.

Snyder, Jason. 2010. "Gaming the Liver Transplant Market." *Journal of Law, Economics, and Organization* 26 (3) (December 1): 546 -568. doi:10.1093/jleo/ewq003.

Swisher, Stephen G., Linda DeFord, Kelly Willis Merriman, Garrett L. Walsh, Roy Smythe, Ara Vaporicyan, Jaffer A. Ajani, et al. 2000. "Effect of operative volume on morbidity, mortality, and hospital use after esophagectomy for cancer." *The Journal of Thoracic and Cardiovascular Surgery* 119 (6) (June): 1126-1134. doi:67/mtc.2000.105644.

Tarnow-Mordi, WO, C Hau, A Warden, and AJ Shearer. 2000. "Hospital mortality in relation to staff workload: a 4-year study in an adult intensive-care unit." *The Lancet* 356 (9225) (July 15): 185-189. doi:16/S0140-6736(00)02478-8.

Teece, David J. 1988. Technological change and the nature of the firm, in: G. Dosi et al., eds., <u>Technical Change and Economic Theory</u>.

Teece, David J., Richard Rumelt, Giovanni Dosi, and Sidney Winter. 1994. "Understanding corporate coherence : Theory and evidence." *Journal of Economic Behavior & Organization* 23 (1). Journal of Economic Behavior & Organization: 1-30.

United Network for Organ Sharing. *2009 Annual Report: Patti Dean's Transplant: Her story is our story.* Richmond, VA. 2009. Doi: https://unos.org/docs/AnnualReport2009.pdf.

United States Department of Health and Human Services, Officer of the Inspector General. 2003. Variation in Organ Donation Among Transplant Centers. Special Report OEI-01-02-00210.

Williamson, Peter, and Markides. "Related Diversification, Core Competencies and Corporate Performance." *Strategic Management Journal* 15 (S2): 149-165.

CHAPTER 2: DOES DISCLOSURE OF CONFLICT OF INTEREST INDUCE COST CONSCIOUSNESS?

THE EFFECT OF PHARMACEUTICAL COMPANY PAYMENT DISCLOSURES ON PHYSICIAN PRESCRIBING BEHAVIOR

I. INTRODUCTION

Few issues are as important to a firm's strategy but so difficult to control as conflict of interest. Conflicts of interest can affect firms at virtually every level of operation, from their suppliers to their employees, even C-suite decision-makers. And such conflicts have the potential to capture value away from a firm at every level as well. In which case, why should conflict of interest ever persist? Why would a firm ever hire an individual who might allow others to capture value away from the firm? Simply put, because they cannot help it. No firm has perfect control over its employees, and the issue of control is particularly difficult in the context of conflicts of interest. At even the simplest level, firms may not have complete control over their employees' incentives; even if they did, it is not always clear whether something truly constitutes a conflict of interest (referred to by Chugh et al as "invisible conflicts"), or whether these activities might actually create value for the firm. For example, having members of management sit on the board of directors: while this appears to be a conflict of interest, many firms believe that there is some value in having management represented on the board (Rechner and Dalton, 1991).

One of the most popular and least controversial methods for dealing with conflicts of interest, regardless of the domain, is disclosure (Moore et al, 2005).While the efficacy of disclosure has been examined in the context of the advisor-advisee relationship—physicians and patients, auditors and investors, lawyers and clients, etc—very little work has been done to explore disclosure's efficacy in an institutional context. To wit, can requiring employees, contractors, etc, to disclose their potential conflicts induce them to realign their incentives with their firm? Can reputational incentives offset external financial incentives? This paper will address this question in the context of physicians and hospitals, where physicians are employees or contractors, and the hospital is the firm. Specifically, I will examine the effect of disclosing pharmaceutical industry payments to physicians on their prescribing behavior.

In-hospital prescriptions constitute an important part of the hospital's cost of inputs, and thus using cheaper (i.e., generic) drugs can have an important impact on a hospital's bottom line. The decision to use generic or branded drugs, however, is made by physicians whose remuneration is rarely directly affected by the cost of the inputs they use. Thus financial relationships with pharmaceutical companies present a tricky problem for hospitals: the promotion practices of pharmaceutical companies do have the potential to create value for the hospital through research funding, trainings, and so forth, but can also capture value away by inducing their physicians to prescribe more expensive, branded drugs. I will examine whether disclosing pharmaceutical industry payments causes physicians to substitute away from branded drugs in favor of generic drugs.

This setting represents a unique opportunity to test the impact of disclosure—the level of detailed data on medical practice allows researchers to examine the details of every day decisions that physicians make, as well as quantify the financial impact of these decisions, in a way that is not possible in perhaps any other industry or type of firm in the United States. Yet even within the medical care setting, testing the impact of disclosure is nontrivial. First is simply the nature of disclosure: in general, physicians are notified that their payments will be disclosed in advance, and so have a chance to modify their behavior prior to observation. I address this issue by exploiting the timing of a settlement between Pfizer and the U.S.

Department of Justice in 2009. The Pfizer settlement presents a unique opportunity to examine this situation: the settlement would require Pfizer to begin publicly disclosing its payments to physicians for the second half of 2009 (beginning in July), while the terms of the settlement were not announced until the following September and affected physicians were not required to be notified of disclosure until December. This creates a period of time where the physicians who received payments may not have known their names would be disclosed, giving us an opportunity to study the effect of disclosure itself.

And while the medical industry does certainly have more specific data than most, data constraints can still present a large impediment to understanding the impact of disclosure. Cross-sectional data can address the aggregate effect of a disclosure policy across all physicians, but if the response of disclosed physicians systematically differs from that of undisclosed physicians, this will not be captured in the results. This research overcomes this obstacle as well by combining two particularly rich datasets. The first is the Dollars for Docs database compiled by ProPublica.org, a Pulitzer-prize winning nonprofit devoted to investigative journalism. The Dollars for Docs database has aggregated information on payments to physicians by all currently disclosing pharmaceutical companies. The data are compiled in a readily searchable format to allow patients (or researchers) to see how much money a doctor has received, when, and from which companies. I have combined these data with the New Jersey Department of Health and Senior Services hospital billing data. This database provides the universe of charges incurred by patients in all hospitals in the state. Each charge includes an identifier for the responsible physician; this identifier allows these data to be matched with the ProPublica data, so that each charge can be classified as coming from a physician who either did or did not have his name disclosed. In combination with the

Pfizer timing, this setting allows us to directly compare the same physician before and after his name has been disclosed.

By overcoming these obstacles, this paper marks a significant contribution to the literature on the efficacy of disclosure. My results show that disclosure in fact causes a slight but significant *increase* in the branded share of prescriptions among physicians whose names were disclosed. Secondly, this paper also notably contributes to the literature by considering theoretically and testing empirically the effect of disclosure on physicians whose names were not disclosed. Consistent with the theoretical model employed here, I find that undisclosed physicians significantly reduce their use of branded drugs in response to disclosure.

Yet while this effects are statistically significant, they may not be economically significant—disclosure was only associated with a 0.6 percentage point increase in the share of branded drugs for disclosed physicians, and a 0.4 percentage point decline in branded drugs for physicians whose names were not disclosed. In dollar terms, this represents a $14 thousand increase and $26 thousand decrease, respectively, for the entire state of New Jersey. If one were to scale these results up linearly to the level of the United States, the impact would be a $443 thousand increase in branded drug spending by disclosed physicians, and $883 thousand decrease by non-disclosed physicians. To provide a sense of scale, total hospital care expenditures in the United States in 2010 were $814.0 billion; the net effect of the Pfizer disclosure on prescription choices is about 5 hundred thousandths of a percent (0.00005%) of this amount. Even the effect on Pfizer itself is miniscule—this reduction represents approximately two thousandths of a percent of their 2010 U.S. biopharmaceutical sales.[14] It has been observed that the provision of information can create value for the firm if the information itself improves decisions, that the improvement has significant value, and that the cost of the information does not offset the value created (Boudreau, 1991). While this paper does not address the costs of implementing such disclosure policies, given the relatively tiny size of the effect, it may well be that the total effect in dollar terms of disclosure is very likely less than the value of the time already spent on discussing it. Given the results demonstrated in this paper, it is highly unlikely that a policy of disclosing conflicts of interest will create (or allow firms to capture) much value.

This paper proceeds as follows: Section II presents some background on the health care industry germane to the study of conflict of interest in a hospital setting. Section III presents the economic model of Bar-Isaac and Deb (in progress) to provide a framework describing the economic tradeoffs implicit in the physician-hospital-pharmaceutical company relationship. Section IV presents the timeline and details of the Pfizer settlement I use for identification of the disclosure effect. Section V then details of the data I use, and Section VI explains the resultant estimation strategy. I present my results in Section VII, and discuss their economic significance in Section VIII. Section IX concludes.

II. Background on the Hospital Industry

Physician Employment: One potential solution to medical conflicts of interest suggested in the literature is simply a more sophisticated contract between hospitals and physicians, one which designs incentives to induce cost-conscious behavior in physicians without banning external financial relationships entirely. To a certain extent, such financial incentives are

[14] 2010 Pfizer biopharmaceutical segment revenues (across all channels, including hospitals) were $25.96 billion in 2010, per their annual report: http://www.pfizer.com/files/annualreport/2010/financial/financial2010.pdf

already being implemented more generally, but not with respect to external conflicts of interest explicitly.

According to the AHA, 45% of physicians are directly employed by or under contract with a hospital. [15] While corporations are not legally allowed to direct or instruct licensed physicians in the provision of care (Hall, 1988), it is acceptable for them to (formally or informally) link renewal of their contracts to cost-conscious behavior (Jensen and Morrisey, 1986). For the majority of physicians who are not employed by hospitals, but rather have admitting privileges that allow them to treat patients in a given hospital, this is not the case. While hospitals may certainly suspend or revoke admitting privileges for these physicians, in general this must be on the basis of the "quality of care, treatment and services […] Decisions which are based upon competitive factors, personal biases, or other similar grounds are not consistent with the obligations of hospitals and physicians involved in the peer review process."[16]

While hospitals may not have complete control for these admitting, non-staff physicians, they may rely on some third-party payers to provide direct cost-consciousness incentives. For instance, fee-for-service physicians may be members or partners in a physician group. Under most types of capitation schemes, these physician groups tend to have "shared risk arrangements" with insurers that generate incentives for the physician group to control costs, which they then pass along to their constituent physicians in the form of bonuses or withheld compensation (Ho, Pakes, in progress; Rosenthal et al, 2002). Extensive data on the rate of capitation agreements is not publicly available, nor included in the data I use here. To provide

[15] American Hospital Association Statistics, 2012.

[16] American Association of Family Physicians, "The Grant or Denial of Privileges."
http://www.aafp.org/online/en/home/practicemgt/privileges/assistancepriv/legalopinion/denial.html

a general idea, the data used by Ho and Pakes (in progress) show that 73 percent of payments to primary physicians by the six largest carriers were in some form of capitation agreement. Thus, while hospitals will rarely have direct financial incentives related to a physician's individual choices, there are a variety of mechanisms through which a physician who fails to be sufficiently cost-conscious overall may be penalized.

Whether such incentives for cost consciousness can be used to directly address conflicts of interest is unclear. Hospitals may try to offer additional monetary incentives to physicians, whether in addition to salaries for employees, or bonuses to physicians with admitting privileges. Yet research has demonstrated in general that gifts are more effective than direct incentives in motivating behavior (Kube, Marechal, and Puppe, forthcoming), and bonuses have been shown to be ineffective at motivating physician behavior even in the absence of any countervailing financial interest (Mullen, Frank, and Rosenthal 2010). Generally speaking, physicians have responded negatively to both bonuses and penalties which they view as impinging on their autonomy and discretion in treating patients (Posner et al, 1995; Mechanic, 2003).

Pharmaceutical Industry Involvement: Pharmaceutical companies frequently make payments to physicians—either as direct compensation for speaking or consulting arrangements, or in-kind in the form of subsidizing trainings, meals, and so forth—that could potentially create a conflict within physicians' relationships with hospitals. Voluntary pharmaceutical industry association guidelines urge that payments to physicians should "primarily benefit patients or be for the education of the physician" (AMA website). As such, many hospitals, physicians and regulators alike hold that these interactions can create value, not just for physicians, but for both hospitals and patients as well. For instance, Chatterji et al

(2008) present evidence that physician involvement with industry in medical device manufacturing leads to innovations with greater impact, creating a beneficial impact for the delivery of health care overall. On the other hand, even gifts or financial considerations that directly benefit patients or hospitals may serve to bias physicians to prescribe more branded drugs. Although many physicians vehemently deny that such gifts will alter their choices in any way, numerous studies have demonstrated that even small gifts can bias the recipient's behavior in ways that the recipient himself does not perceive (see Dana and Loewenstein, 2003 for a review).

Hospital Finances: Hospitals may have a variety of payment agreements with physicians, almost none of which are visible to the public. In the case of fee-for-service arrangements, in which hospitals simply bill either the insurer or patient for each item used while the patient was in the hospital, the hospital may be able to recoup the higher cost of branded drugs. If, however, the insurer has negotiated prices for drugs based on the molecule itself, then if the physician uses a brand name version the hospital may not be able to bill for the higher cost. Another very common type of agreement between insurers and hospitals is prospective payment. Under prospective payment—employed by Medicare, Medicaid (in some states) and some private insurers such as HMOs—hospitals will be paid a fixed sum based on diagnosis itself, and any remainder after treating the patient will accrue to the hospital as profit. While the physician's services are rarely if ever included in this flat fee, inputs such as drugs administered during the hospital stay are included.[17] As such, a physician's choice to use branded drugs instead of generic will directly affect the hospital's bottom line but not a

[17] Self-administered drugs that the patient acquires through pharmacies are generally not included in this fee, but this cost is almost entirely borne by patients or their insurers if they have prescription benefits.

physician's. There are a variety of other flat-rate reimbursement schemes—per diagnosis, per day, per case, per episode of care—in which this will be the case.

As such, inducing physicians to administer more branded drugs to patients effectively transfers value to the pharmaceutical company at the expense of the hospital; more expensive treatments (including drugs) will eat into the hospital's bottom line. Yet since the gifts themselves may also help create value for the hospital, it is not at all clear whether the net effect of these gifts creates value for or captures value away from hospitals. Thus, many private hospitals are reluctant to institute an outright ban on these relationships; given the difficulties with designing appropriate financial incentives for physicians outlined above, disclosure has been a popular suggestion for how to deal with this problem.

III. ECONOMICS OF DISCLOSURE AND REPUTATION

For patients, disclosure allows them to appropriately discount the advice that they receive (Cain et al, 2005). But for a large hospital that may see upwards of a hundred patients per day, assessing every prescription written for potential bias would be hugely resource-intensive. Furthermore, given the often time-critical nature of the care delivered in hospitals, auditing these decisions prior to the actual delivery of care is simply not feasible. The purpose of disclosure from the hospital's perspective is rather to gain information about a physician's overall "type" or preference for branded drugs. In turn, physicians will be shamed into minimizing financial relationships and being more attentive to the potential for bias, or at least the appearance of bias (Cranston, 1979; Melo-Martin and Intemann, 2009).

The use of shame to regulate behavior is reminiscent of the extant literature on reputation. This work largely ignores, however, situations in which a) disclosed conflicts may not be uniformly perceived as shameful or evidence of being "low quality"; b) external financial incentives are not fixed, and will likely also be affected by an agent's reputation. Theoretical models of disclosure that have focused on the advisor/advisee relationship have largely neglected these trade-offs. Empirical evidence on the effect of disclosure in such organizational settings is also quite sparse, but evidence from lab studies suggests that disclosure does not have a bias-reducing effect. In fact, individuals whose names are disclosed may in fact bias their advice even more (Loewenstein, Cain and Moore 2005; Loewenstein, Sah and Cain, 2012). Given these inconsistencies, a model that is more sophisticated than these explanations is necessary to understand how disclosure affects physicians.

There are two alternative streams of organizational economics literature relevant to this setting. The first is common agency; papers in this literature deal with an agent who faces multiple principals with heterogeneous objectives (Segal, 1999; Hart and Tirole, 1990). In this case, the agent is the prescribing physician, facing a hospital that prefers fewer and lower cost drugs to be used, and a pharmaceutical company that prefers that their branded drugs be used. The difficulty with using this type of model to generate predictions is the pervasive assumption that explicit incentive contracts can be written by either or both of the principals. As outlined in the previous section, hospitals typically have limited power over physician incentives, and generally have to resort to blunt instruments such as the termination of contracts entirely. For pharmaceutical manufacturers, although they observe physician prescribing behavior, directly incentivizing physicians in a "pay for play" type arrangement is illegal in the U.S. under anti-kickback statutes.

In the absence of direct monetary incentives, one might look to a reputation/career concerns model for insight. With a few recent exceptions, however, most of this literature focuses on how an agent can signal that they are a universally-preferred high quality type. In this case the different principals (hospitals and pharmaceutical companies) prefer different types of physicians. The hospital prefers physicians who do not have a preference for branded drugs, while the pharmaceutical manufacturer prefers physicians who do. In contrast with traditional reputation models, there is no universally preferred "high quality" type; in this setting types do not correspond to quality, but rather to preferences. I will therefore use the reputation model of Bar-Isaac & Deb (work in progress) that examines such a situation.

In this model, physicians can be one of two types—they can have a preference for either branded or generic drugs, denoted as types (θ_B, θ_G). Each physician is observed by two audiences—the pharmaceutical manufacturer and the hospital. Each physician has a choice of actions for each prescription decision: prescribe a branded drug (a_B), prescribe a generic drug(a_G), or some compromise solution (a_P). This compromise could exist in pure strategies in the form of a pseudo-generic,[18] which represents some measure of cost-consciousness (by choosing a drug that is cheaper than a branded drug) but also brand consciousness (by staying loyal to the original manufacturer). Thus the compromise action is not a clear signal of either type of physician. There is no effort cost for an action congruent with a physician's type, that is, for physicians of type θ_B, action a_B is costless. The cost of effort for both types is positive for the intermediate action, but less than it would be for the extreme opposite action (i.e., $c(a_B, \theta_G) > c(a_M, \theta_G)$). This is not to say that a physician of type $\theta_B$will always prescribe branded drugs, but rather, when the best course of treatment is uncertain (which happens quite frequently in medical care), the $\theta_B$physician will prescribe a branded drug first, and vice versa. This characterization of physician preferences for either branded or generic drugs is consistent with previous empirical work (Hellerstein, 1998; Gonzalez et al, 2008).

[18] A drug manufactured by the same firm that holds a patented drug, once the drug goes off-patent.

In this setting, rather than paying wages according to observed output, the different principals pay the agent according to their beliefs about the agent's type. This more accurately reflects the nature of the relationship between a pharmaceutical company and a physician, where companies will expend additional effort and resources to "maintain a good relationship" with physicians they believe will prescribe their drugs in the future.[19,20] This is also a good approximation of most physician-hospital relationships. Whether by the hospital directly or participation in a physician's group, he will likely be evaluated against overall targets of cost-consciousness rather than paid a wage according to each individual prescription (Rosenthal et al, 2002).

Under separate observations (i.e., no disclosure) neither type will ever choose to pool on the compromise action, while under common observations, there is an equilibrium under which both types will play the compromise action for both audiences, as long as the different audiences still have some uncertainty about their type. The implication for this setting is that under no disclosure, physicians have no incentive to modify their behavior when being observed by the audience that prefers their type; simply following their own preferences "would increase the [physician's] payoff from one audience without adversely affecting the payoff from the other." (Bar-Isaac & Deb). The introduction of disclosure introduces the possibility of an adverse effect, and thereby introduces equilibria in which physicians would pool by choosing the compromise, even when being observed by an audience that prefers their type. For example, a type θ_B physician will never choose the compromise action when he is

[19] Interview with pharmaceutical sales representative.

[20] This model assumes that types are fixed and exogenous. This avoids the question of how much a physician's underlying preferences may be determined by the payments themselves; e.g., whether payments over time might "convert" a physician from a generic type to a branded type is not addressed.

not observed by the hospital (e.g., prescriptions for the patient to fill on his own in a pharmacy).

The health care industry, particularly hospitals, differs slightly from the setting proposed by Bar-Isaac & Deb in the order of disclosure and the nature of the information disclosed. Namely, the model does not allow for asymmetric disclosure in which one principal has full information and the other principal only limited information. Furthermore, in their model disclosure allows for all audiences to observe all tasks. In contrast, within hospitals there is typically asymmetric disclosure: pharmaceutical companies are aware that physicians are employed by hospitals and can observe their prescribing records,[21] while hospitals may be unaware that a physician is being paid by a pharmaceutical company. Additionally, disclosure in this setting makes hospitals aware of which physicians are receiving payments from pharmaceutical companies, but does not allow hospitals to observe the physician's full action set (namely, prescription decisions made outside the hospital).

These distinctions are not particularly difficult to reconcile with the model, fortunately. Where under separate observations neither agent has an incentive to play the compromise action, under asymmetric information the compromise action becomes a feasible outcome prior to the disclosure event. The agent with a type that is incongruent with the audience with full information (in this case, type θ_G) will have the same payoffs as under symmetric information, and thus may choose to play the compromise action to either audience. For type θ_B, asymmetric information introduces the possibility of playing the compromise action while at the hospital, but not elsewhere.

[21] Health information organizations such as IMS Health "combine prescription information purchased from pharmacies with anonymized patient medical records purchased from health insurance companies to determine which drugs individual physicians prefer for specific diagnoses and patient populations" (Fugh-Berman, 2008). These data are available across all channels through which prescriptions are filled, including hospitals.

Under disclosure, although hospitals do not observe more tasks than they did prior to disclosure, they are given information that allows them to update their beliefs about physician's preferences. While it is not clear exactly how informative hospitals find this signal, it is clear that a payment from a pharmaceutical company is a much stronger (and more precise) signal of a branded preference than any single prescription that a physician may write. This changes the available equilibria somewhat, in that physicians would have to substitute more heavily toward the compromise action than they would in the Bar-Isaac and Deb model in order to achieve a pooling equilibrium.

This model illustrates the difficulty in generating a single prediction *a priori* on the net effect of disclosure, in that both pooling and fully separating equilibria exist under both common and separate observations. That is, in the hospital setting it is entirely possible for there to exist either a pooling equilibrium in which all physicians choose the compromise action or a separating equilibrium in which physicians simply reveal their types by choosing their costless actions. The Bar-Isaac and Deb model identifies a total of five potential equilibria under both separate and common observations, with a total of 16 potential combinations between the pre and post periods. Fortunately, it is possible to use the features of this setting to narrow down the potential predictions considerably. First, the incentive to cater to pharmaceutical companies may decrease after disclosure, due to the possibility of alienating hospitals; it is highly unlikely to increase given that the pharmaceutical companies' ability to observe physicians remains unchanged. Thus, I can eliminate any equilibrium-pairs that assume that physicians will cater *more* to pharmaceutical companies after disclosure than before.

While this goes a long way to narrowing the set of potential equilibria, it still does not make the theoretical impact of disclosure immediately clear: among those that remain, one could expect that physicians who received pharmaceutical payments may remain unchanged, increase the share of prescriptions for branded drugs, or reduce it. Physicians will reduce their branded prescriptions in the event that disclosure induces physicians to choose the compromise action. This is both congruent with conventional wisdom (disclosure will induce cost-conscious behavior), as well as the model—agents strictly prefer reputational pooling equilibria as long as they are available. If, however, disclosure induces degenerate beliefs (i.e., causes the hospital to become as good as certain about the physician's type), then disclosed θ_B physicians will instead *increase* their branded prescriptions.

The crucial question here is whether a compromise equilibrium exists under disclosure. The answer to this question depends on two things: namely, do the payoffs from concealing their types outweigh the cost of the strength of the signal these pharmaceutical payments send? And how strong is the signal that receiving pharmaceutical payments sends? If the knowledge that a doctor received payments from pharmaceutical companies causes a patient or hospital to become almost certain that the physician is type θ_B, then the physician no longer has any incentive to modify his behavior to signal otherwise. In this case, while a type θ_B physician had no incentive to directly cater to the hospital's preference, he may have prescribed more pseudo-generics to patients in the hospital to conceal his type. If the disclosure of payment information effectively reveals his type, then the lack of reputational motivation would cause physicians who received payments to increase their rate of branded drug prescription.

Unfortunately, there are no clear answers to these questions. The attitudes of hospital administrators and managers have largely been ignored in the discussion of disclosure. Multiple surveys have assessed patient reactions to disclosure of pharmaceutical payments, but even these do not paint a consistent picture: in a recent review of the literature addressing patient attitudes toward physician financial ties to the pharmaceutical industry, they document that the percent of patients who believe financial ties decrease the quality of care or affect prescribing behavior ranges anywhere from 27% (Tatterstall et al, 2009) to 70% (Blake and Early, 1995). Therefore it would be difficult to use patient reactions even as a proxy for the beliefs of hospital administrators; the question will have to be addressed empirically.

This model also calls attention to an important, but previously neglected, empirical point: the effect of disclosure on physicians whose names are not disclosed. Among the possible equilibria, the model predicts that other physicians may not alter their behavior, or they may reduce their branded prescriptions. Because this question has not been previously addressed empirically or theoretically, it is impossible to determine which is the more likely outcome. From the perspective of a hospital or policy maker, the net effect of the policy, rather than the particular individuals affected, is what matters most. Distinguishing between the effect on different groups of physicians, however, will be important in understanding the mechanics of how disclosure affects (or fails to affect) the behavior of physicians.

IV. TIMELINE OF THE PFIZER SETTLEMENT

In financial statements in Q2 2008, Pfizer disclosed the $2.3 billion fine imposed by the United States Department of Justice (DOJ), related to improper promotion to physicians of their anti-psychotic medication Bextra. Although this information was available in their SEC filings, they did not issue any press release, and no details of the settlement (beyond the dollar value of the fine) were disclosed publicly. In February 2009, Pfizer issued a press release stating its intention of voluntarily disclosing payments to physicians, to begin in early 2010, but which payments were going to be disclosed were still under consideration. On September 2nd, 2009 the D.O.J. publicly announced the details of their settlement with Pfizer. The press release stated that Pfizer would pay $1.3 billion for the case related to Bextra, and

> In addition, Pfizer has agreed to pay $1 billion to resolve allegations under the civil False Claims Act that the company illegally promoted four drugs – Bextra; Geodon, an anti-psychotic drug; Zyvox, an antibiotic; and Lyrica, an anti-epileptic drug – and caused false claims to be submitted to government health care programs for uses that were not medically accepted indications and therefore not covered by those programs. The civil settlement also resolves allegations that Pfizer paid kickbacks to health care providers to induce them to prescribe these, as well as other, drugs. (Health and Human Services Press Release, 9/2/2009).[22]

As part of the settlement, Pfizer signed a Corporate Integrity Agreement drafted by the DOJ. While this was not novel in itself—Pfizer representatives had signed such an agreement in 2004 as part of a similar settlement for the inappropriate promotion of Neurontin, an epilepsy drug allegedly promoted as a painkiller—as a result of the kickback allegations, the 2009 agreement mandated that Pfizer begin disclosing payments made to physicians. According to the agreement, dated August 31st and released on September 2nd, any physician who had received gifts or remuneration amounting to $500 or more during the last two quarters of 2009 would have his name and the total value of gifts or payments he received disclosed. Beginning in 2010, all payments of greater than $25 would have to be disclosed. Disclosure was not immediate, however; the settlement gave Pfizer until December 31st to notify any physician they had contact with, and until March 31st, 2010 to disclose the payments made in 2009.

[22] http://www.hhs.gov/news/press/2009pres/09/20090902a.html

Because payments going back to July would have to be disclosed, while the physicians did not have to be notified of disclosure until December, this creates a unique opportunity to observe the impact of disclosure on physician behavior. In this case, the timing of the Pfizer disclosure policy has created a "pre-disclosure" period during which we can observe the behavior of physicians whose names would be disclosed in the future, before they knew that their names would be disclosed (see Figure 1). I categorize three distinct periods: pre-disclosure, the six month period in which physicians did not know that their names would be disclosed; disclosure threat, the four months following in which physicians knew that their names would be disclosed, but were not yet public; and post-disclosure, the months following the publication of the physicians' names on the Pfizer website. [23]

V. DATA

In order to test the effect of the disclosure of payments on physician prescribing behavior, I use data provided by the New Jersey Department of Health and Senior Services UB-92 dataset, which records all patient discharges from hospitals in New Jersey, for the years 2008-2010. [24] Detailed information is collected for each discharge, including the identifier of the attending physician; the charges for the visit, including itemized breakdown of charges associated with different services; a detailed breakdown of payment, including health plans that provided coverage, the total amount paid (rather than what was initially billed), the patient's contribution, and so forth; patient demographics; and all diagnoses recorded during a given visit, as well as procedures. In this setting I am particularly interested

[23] It is worth noting that I infer the extent of physician knowledge based on Pfizer's public statements. It is possible that physicians may have known or suspected that their names would be disclosed due to non-public communications between Pfizer representatives and physicians. Additionally, while the Corporate Integrity Agreement was much more specific about which types of financial arrangements Pfizer would be required to disclose, Pfizer's "voluntary" disclosure announcement in February may have alerted some physicians that their names would likely be disclosed. See Appendix for more details.

[24] Excluding psychiatric hospitals.

in charges for prescription drugs. These data do not include prescriptions written by physicians that patients fill themselves at a pharmacy; the only drug charges recorded in these data are for those drugs that are administered to the patient while in the hospital. While this significantly understates the overall use of prescription drugs, it is the appropriate metric for this setting because only drugs administered while in the hospital—and thus included as inputs as part of patient care—will be relevant to the hospital's bottom line.

Using data from the National Plan and Provider Enumeration System, I have added additional data on the attending physician associated with each visit, namely his or her specialty (i.e., health care provider taxonomy codes), gender, and whether he or she is a sole proprietor. [25] Finally, I added information for each physician on whether he or she received payments from Pfizer, as well as any other pharmaceutical company disclosing payments, using payment information collected by ProPublica. ProPublica is a Pulitzer-prize winning non-profit investigative organization that has aggregated the information on payments to physicians published by individual pharmaceutical companies (http://www.propublica.org/series/dollars-for-docs). While most of these companies are required to make this information public by similar, subsequent settlements with the Department of Justice, they are very difficult to find and generally not searchable. In the interest of genuine transparency and ease of patient access, ProPublica has aggregated the data published by all pharmaceutical companies currently reporting payments. Chart 1 summarizes the companies reporting as of September 2011. These firms accounted for "about

[25] Administered by the Centers for Medicare and Medicaid, https://nppes.cms.hhs.gov/

40 percent of the U.S. market in 2010" ("About the Dollars for Docs Data," ProPublica, 2011).[26] Table 1 provides descriptive statistics on these payments at the physician level.

The billing data are reported by NJDHSS at the patient visit level. Each diagnosis is classified by an International Classification of Diseases (ICD) code, as published by the U.S. Public Health Service. These codes can be up to six digits long; I aggregate these to the 2-digit level.[27] Because I am primarily concerned with the behavior of physicians, I have aggregated these data to the level of the doctor-hospital-diagnosis for each month. This allows us to examine how the behavior of a given doctor changes within a diagnosis, thus eliminating any concerns over variation within the patients' disease profile. I begin with 12 million patient visits for 18 thousand physicians from 2009-2010. After discarding observations for visits prior to July 2009 (when payments began to be recorded), and collapsing these to the doctor-hospital-diagnosis-month level, I am left with 2.0 million observations across the three periods. Of these, 93% come from physicians who never administer drugs to any patient while in the hospital. There are 140,576 observations from 3,080 physicians who administered a drug in the hospital. Among these, 1,430 observations are from 28 physicians matched to the ProPublica data on Pfizer payments.[28] Table 2 summarizes the descriptive statistics for key variables in the data.

VI. Estimation Strategy

[26] http://www.propublica.org/article/about-our-pharma-data

[27] ICD-9 codes are similar to industry classification codes in that additional digits provide additional detail about the disease. For instance, diseases of the respiratory system are ICD codes 460 to 519; codes beginning with 46 (460-466) are acute respiratory infections; 466 is acute bronchitis and bronchiolitis; 466.11 is acute bronchiolitis due to RSV, etc. While the full ICD-9 code is significantly more granular than the two digit level, and therefore would increase the total number of observations, it would also result in a highly imbalanced panel

[28] 139 individuals were originally identified as receiving Pfizer payments of $500 or greater in 2009.

The timing of the Pfizer disclosure lends itself naturally to a differences-in-differences estimation strategy. That is, I can specify a straightforward OLS regression that includes fixed effects for both physician and diagnosis; by then interacting Pfizer payment status with the disclosure periods outlined above, I will estimate the effect of disclosure for a particular doctor in a given hospital treating a particular diagnosis. In order to estimate the effect of disclosure on physician's prescribing behavior, I will use the share of prescriptions that are branded drugs as the dependent variable. Table 3 gives details on branded prescription share by disclosure period and Pfizer payment status. Notably, the mean share of branded prescriptions for Pfizer physicians is not significantly different between the "Pre" and "Threat" periods.[29]

The specification for a given physician *i* treating diagnosis *j* at hospital *h* in period *t* is

$$Share\ of\ Branded\ Drugs_{ijht} =$$

$$\beta_0 + \beta_1 Pfizer_i + \beta_2 Disclosure\ Period_t + \ \beta_3 Disclosure * Pfizer +$$

$$\beta_4 Patient\ Profile_{ijt} + Diagnosis_j + Month_t + Month_t^2 * Hospital_h + Physician/$$

$$Hospitalijh{+}\varepsilon ijht$$

To account for overall time trends, such as the introduction of new drugs while other drugs go off patent, I include a fixed effect for each unique month-year combination. I include the physician's patient profile (i.e., the percent of a physician's patients who were female, black, white, Asian, had an HMO as their primary payer, or were inpatients) at a given

[29] The current specification defines the pre-disclosure period as ending when the physicians would have to be notified of disclosure. As a robustness check, I also ran the specifications described above, modifying the pre-disclosure period to end as soon as the terms of the settlement were announced (September 3rd, 2009). While the results were similar in both direction and magnitude, narrowing the pre-disclosure period to only two months eliminated too many physicians and diagnoses for any of the results (even unrelated to disclosure) to be significant.

hospital in a given month. I include these patient demographic characteristics (all of the demographics available in the data) to control for any possible variations in patient preferences for certain drugs. Similarly, the indicator for an HMO as a primary payer may be an important determinant of reimbursement or externally imposed cost-consciousness, and an increase in HMO patients could easily have an effect on a physician's overall use of branded drugs. I also include the admission status of patients (i.e., inpatient versus outpatient); this is an important indicator of acuity, but also in many cases affects the reimbursement arrangements between hospitals and insurers.

The inclusion of a fixed effect for each physician-hospital pair will capture each physician's time- and diagnosis-invariant preferences for either generic or branded drugs as well as any hospital-level policies on generic substitution. The inclusion of a separate fixed effect for every unique physician-hospital pair will absorb any heterogeneity caused by different financial relationships between physicians and hospitals. This controls for any alternative financial relationships within different physicians in a single hospital, as well as a single physician having multiple distinct financial arrangements with different hospitals. The hospital fixed effect will account for any variation in hospital policies, but does not address any hospital-specific time trends in substitution policies. To resolve this issue, I include a quadratic month variable interacted with each hospital fixed effect. As noted in Snyder (2010), while this is somewhat restrictive in that it imposes a quadratic structure on the effect of time, it is preferable to omitting a time-hospital interaction entirely.

In keeping with previous empirical work, I do not vary the physician's preference over time. While a physician's preference may itself be affected by the receipt of payments from a pharmaceutical company, this will only affect the results of this estimation if there is some alteration in a physician's underlying preferences for generic versus branded drugs that is correlated with but causally unrelated to disclosure itself. The inclusion of physician fixed effects are particularly important because even if physicians are unaffected by payments from pharmaceutical companies, these physicians also differ from physicians who have not received payments in other dimensions that may affect the taste for branded drugs (see Table 4). The inclusion of a diagnosis fixed effect is similarly crucial in capturing the availability and appropriateness of generic and branded options to treat a given diagnostic class. Ultimately the final specifications include 3,502 doctor-hospital pairs, 108 ICD codes, 18 month dummies, and 125 hospital*month^2 dummies.

VII. RESULTS

Table 5 summarizes the differences-in-differences regressions using these dependent variables. The coefficients reported in Table 5 can be interpreted as the effect of each variable on the rate of prescribing within the patients of a given doctor working on a particular diagnosis in a particular hospital. Model 1 presents the simplest regression, summarizing the effect on physicians without controlling for overall time trends or patient characteristics—this is simply the change within a physician-hospital pair, for a given diagnosis. Model 2 introduces month fixed effects, and Model 3 controls for the composition of patient characteristics that a physician sees. Model 4 introduces the quadratic month-hospital interaction. Finally, Model 5 includes analytic weights to account for the actual number of patients that a physician sees in a given month (i.e., in the previous regressions, I examine the mean share of branded drugs for a physician in a given month; whether that physician saw one patient or thirty, he or she enters the regression equally).

The inclusion of analytical weights does increase the size and significance of the coefficient on Pfizer physicians in the post-disclosure period slightly; however, both the magnitude and significance of the effect are largely unchanged by the inclusion of these alternative controls. In each specification, among Pfizer physicians the post-disclosure period is associated with a small but significant increase in the share of branded prescriptions that a physician administers, relative to the pre-disclosure period. In every model the coefficient for Pfizer physicians in the post-disclosure period is significantly (at the 99% level) different from the coefficient for non-Pfizer physicians in the same period. The disclosure threat period, however, is never associated with a significant effect for Pfizer physicians.

The impact on physicians who did not have their names disclosed is less clear cut. The disclosure threat period is significantly associated with a decline in branded drugs relative to the pre period by non-Pfizer physicians in Models 1 through 5. Although the magnitude of the effect is sensitive to the inclusion of alternative time controls, the decline is still significant at the 95% level in the fully-specified Model 5. Similarly, the post-disclosure period is associated with a decline in the share of branded drugs used by non-Pfizer physicians, but the effect is not significant after the inclusion of a hospital specific time-trend and patient-weights.[30] Due to the noisiness of the effect on Pfizer physicians, the effect is not significantly different between Pfizer and non-Pfizer physicians in the disclosure threat period, although they are significantly different in the post-disclosure period. These results are consistent with a separating equilibrium after disclosure: non-disclosed physicians decrease

[30] As a robustness check, I test the effect of using alternative specifications of a time trend (seasons, fixed effects for periods with multiple patent expirations, omitting the hospital time trend, and so forth). The alternative specifications were too numerous to be presented here, but the results are robust to these alternative specifications. Details are available from the author.

their rate of branded drug prescriptions, while the net effect for disclosed physicians is a small but significant increase in branded prescriptions.

Tables 6 and 7 recreate Models 3-5 but lend greater detail in order to examine whether subsets of non-disclosed physicians are reacting in different ways. As part of their settlement, beginning in 2010 Pfizer would have to track and subsequently disclose payments as low as $25. Thus, physicians who received payments in 2010 would have their names disclosed in 2011. It is not possible to tell whether these physicians also received payments in 2009, or when exactly in 2010 they received payments. The threat and post periods, however, all constitute a “threat” period for these physicians, and could affect their behavior. It is possible that the imprecision in the estimates of the disclosure period on all physicians reflects heterogeneous responses by different types of physicians among those whose names had not been disclosed.

Table 6 breaks out the effect of the disclosure on physicians who were not disclosed for accepting payments from Pfizer in 2009, but would have their names disclosed in 2011 for payments made in 2010. While these physicians may not have received payments at the time of the disclosure announcement, it is probable that some of these physicians did receive payments in 2009 that were not above the $500 cut off for disclosure in that year. Thus for these doctors, the post-disclosure period is in fact part of an extended disclosure-threat period. In each of models, there is no significant effect of disclosure on physicians who received payments in 2010, but had not yet been disclosed. This is consistent with the absence of an effect in the threat period for disclosed physicians. Table 7 expands this to examine the effect on physicians who received payments from any company that would be disclosed in 2010. While only Pfizer physicians were required to be notified of the terms of disclosure according to the periods specified here, it is possible that physicians who accepted payments from pharmaceutical firms not yet disclosing their payments may react to the disclosure of their peers. As for Pfizer physicians who would not be disclosed until the following year, however, there is no significant effect.

Finally, Table 8 lends further granularity to the disclosure status of physicians whose 2009 payments from Pfizer were disclosed. As of 2009, Cephalon, Eli Lilly and GlaxoSmithKline were already disclosing payments made to physicians; of the 1,430 observations from Pfizer physicians in these data, 845 came from physicians whose names had already been disclosed as receiving payments from one of these other firms. Table 8 summarizes the main results as in Table 5, but with the added detail of breaking out the effect on physicians whose names would only be disclosed by Pfizer (Pfizer 2009 Only), and those for whom Pfizer would not be their first disclosed payment (Pfizer 2009 and Other 2009 payments). The effect of disclosure on physicians for whom this will be their first disclosure drops down to .003 (significant at the 94% level without patient weighting, and at the 97% level with weighting). For physicians whose names have already been disclosed, the effect appears to be even larger (.010 with patient weighting). This lends further support to the idea of a separating equilibrium: for physicians who have accepted multiple payments, the probability that they will be able to prevent the principals from learning their types through their prescription decisions has dropped even further, and thus they are even more likely to revert to their costless action.

VIII. Economic Significance of Disclosure

While the effect of disclosure on both disclosed and undisclosed physicians is statistically significant, the magnitude of the effect is quite small. The effect on disclosed physicians was a 0.6 percentage point increase in the share of branded prescriptions in the post-disclosure period, as compared with the pre-disclosure period. Pfizer physicians administered drugs to patients 1,296 times in the pre-disclosure period, so this represents an increase of 7.78 patient prescriptions. In the same period, the average charges for branded drugs were $932 higher than for generic drugs among Pfizer physicians. Taken together, this implies an increase in annual drug spending in New Jersey of only $14,494. In contrast, I find that disclosure is associated with a 0.4 percentage point decline in branded drugs during the threat period for physicians whose names were not disclosed, and no significant effect in the post-disclosure period. Given the 41,448 patients administered drugs in that period, this represents a reduction of 165.79 patient prescriptions. The gap in drug charges is not so large for the non-Pfizer physician population, however—branded charges are only $159.74 greater than generic on average—but this still translates to an annual savings across New Jersey of $26,484, or a net savings of $11,990.

Even if one were to extrapolate these results to the national level, the impact is not that large. New Jersey is home to slightly less than 3 percent of the total population of the U.S. If one simply divides these results by 3 percent, then the total increase in pharmaceutical spending by Pfizer physicians will be $483,149 annually, while non-Pfizer physicians will reduce their spending by $882,787. Based on this simple approximation, the cost savings would be less than half a million dollars nationwide. To provide a sense of scale, Pfizer's sales in the US in 2009 were $25.96 billion; in a worst case scenario for Pfizer, if all of the reduction of branded drugs were due to physicians switching away from Pfizer drugs specifically, their total US revenue would decline by two thousandths of a percent. From the hospital services perspective, total hospital care expenditures in the United States in 2010 were $814.0 billion; the net effect of disclosure is about 0.00005 percent of this amount.

IX. CONCLUSIONS

This paper demonstrates that while disclosure of pharmaceutical industry payments results in an increase in the rate of branded prescriptions by the disclosed physicians, it is also associated with a decrease in branded prescriptions by non-disclosed physicians. In some sense, the conventional wisdom—that disclosure of conflict of interest should reduce medical costs—is correct. However, the mechanism by which disclosure achieves this reduction in costs is clearly not what was expected. These results are, however, consistent with a shift to a separating equilibrium, as suggested by the model of Bar-Isaac and Deb. This suggests that disclosure may reduce the incentive or inclination of physicians to choose reputation over their individual preferences.

These results further suggest that if a large number of employees are implicated in conflicts of interest, it may not be worth the cost or trouble for firms to attempt to use disclosure to counteract these. Without a relatively larger group of workers trying to distinguish their behavior from that of the disclosed workers, the cost-saving effects of disclosure may be eclipsed by the reduction in cost-saving behavior from disclosed workers. This finding may also help to reconcile some seemingly contradictory previous work on disclosure. Studies done in the lab (Cain, Loewenstein and Moore, 2005) have demonstrated that disclosure of conflicts of interest resulted in large increases in bias, either from moral licensing or strategic exaggeration. In contrast, another study of the effect of disclosure laws at the state level have shown that the effect of disclosure varies and may be insignificant depending on the comparison state; the results that are significant demonstrate a net reduction in the use of branded drugs (Pham-Kanter et al, 2012). The findings presented here suggest that these results may not be incompatible. Rather, physicians whose names were actually disclosed may be exhibiting a large increase in their branded prescriptions, while non-disclosed physicians offset this with decreases in their branded prescriptions.

The results presented here do not address the cumulative effect of disclosure. They are, however, quite suggestive for further work in the field. For instance, I find that the cost-saving effect of disclosure on non-disclosed physicians is more of a dip after disclosure announcement that did not persist through the post-disclosure period. For disclosed physicians, in contrast, the increase in branded prescriptions was even greater for physicians whose names had already been disclosed. While this study does explicitly address the long-term effects of disclosure, these results suggest that increasing prevalence of disclosure may in fact increase health care costs. For fields such as health care where consumer protection is an important policy goal, this is a crucial phenomenon to understand, even if the economic significance is small. For firms in other industries looking to disclosure to help realign their employees’ incentives, they may do better to look elsewhere.

APPENDIX

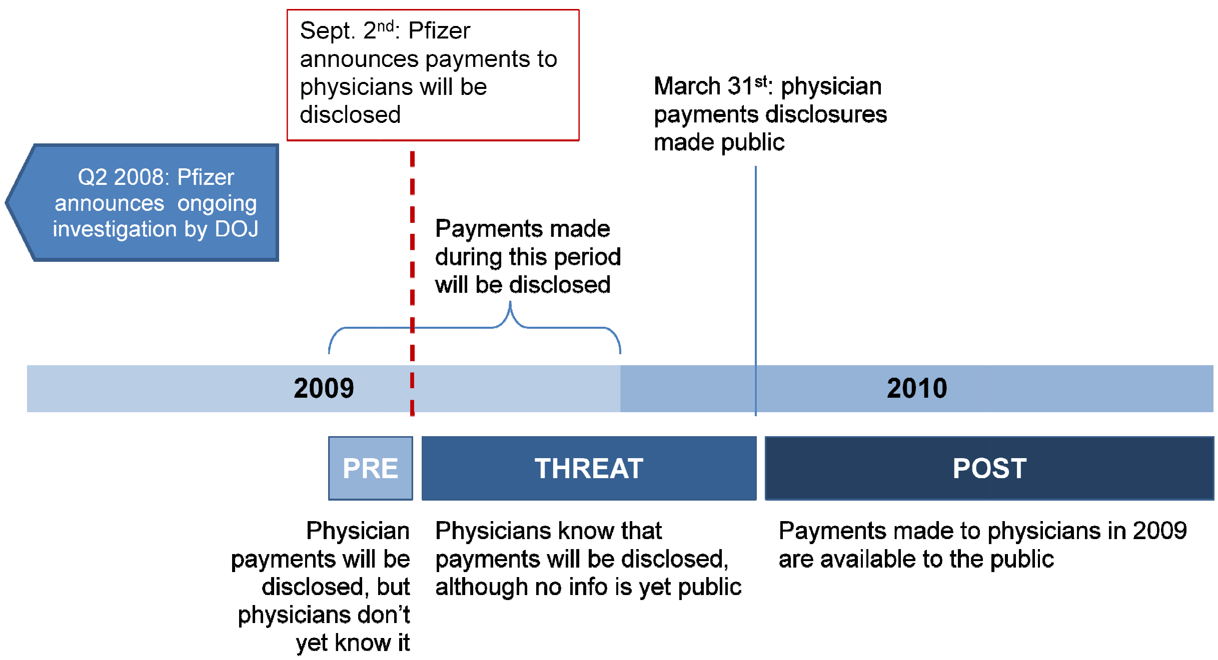
As noted in the paper, there is some concern as to whether Pfizer physicians may have been alerted to the substance of Pfizer's settlement with the DOJ prior to official notification. While it is not possible to control for private communications between Pfizer and the physicians they paid, I can examine whether any public communications—namely, the announcement that they intended to begin "voluntarily" disclosing payments—had an effect on Pfizer physicians. This announcement omitted a number of the details relevant to whom exactly would be disclosed. Furthermore, given that this announcement was voluntary, Pfizer had no obligation to (nor announced any intention to) inform physicians. The public coverage was sparse—a LexisNexis search for the terms "Pfizer," "physician" and "disclosure" in the two months following the date of the announcement (February 9th, 2009 to April 9th 2009) yields five articles in the U.S. press. Of these, only two actually refer to Pfizer's disclosure policy: a blurb in the publication Pharma Marketletter (on February 10th), as well as a mention in a New York Times article (on March 4th) about investigations into surgeons who demanded kickbacks from pharmaceutical and medical device manufacturers.

It is still possible, however, that physicians who received money from Pfizer were made aware that their names could or likely would be disclosed. To address this question, I examine the effect of this announcement on Pfizer physicians. I examine this using the same setting as in Model 5 in the tables presented previously, changing only the disclosure period. In this case, the pre and post periods are defined as the months before and after the announcement to see if physicians whose names would be disclosed in 2010 modify their behavior. As an additional check, I include the same specifications following the New York Times mention of the policy on March 4th.

The Appendix table presents the effect of the Pfizer press release and the New York Times article. I vary the length of the pre- and post-periods to one, two or four months to examine whether any effect is apparent in the short run or slightly longer run. The pre- and post-periods are symmetric, that is a one month period indicates that the month after the announcement is compared to the month prior. One month periods allow for no overlap between the pre- and post-periods of the Pfizer press release and the New York Times article. In terms of estimating the effect of each of these on physician behavior, time periods which do not overlap are preferable. However, given the large number of fixed effects included in the specification, narrow time windows can result in noisily estimated parameters due to imbalanced panels. No physician in the data admits patients to a hospital in every single month of the data, and some diagnostic categories are significantly less likely to appear in some months rather than others. Thus, it will be important to also include longer periods to verify any results. Four months is the longest period one can test after the New York Times article (March through June) without significant overlap with the pre-disclosure period as defined in the rest of this paper. I additionally include a two month period to examine the effect of an intermediate period length. While the magnitudes of the coefficients vary both across the period length and the announcement type, none of the results are significant.

FIGURE

Figure 1: Timeline of Pfizer Settlement



TABLES

Table 1: Descriptive Statistics on Payments Received per Physician

		Mean	St. Dev.	Minimum	Maximum
Among all physicians	Total Amount 2009	$ 89.64	$ 1,473.08	$ -	$ 126,413
	Total Amount 2010	$ 218.58	$ 2,964.30	$ -	$ 427,246
	Amount received from Pfizer 2009	$ 14.70	$ 618.03	$ -	$ 53,605
	Amount received from Pfizer 2010	$ 62.14	$ 1,837.48	$ -	$ 427,246
	Amount of payments already disclosed in 2009*	$ 71.61	$ 1,259.44	$ -	$ 126,413
	Company count 2009	0.018	0.157	0	4
	Company count 2010	0.292	0.602	0	7

Observations: 2,005,141

Among physicians who received those payments	Total Amount 2009	30,222	$ 5,947.62	$ 10,446.66	$ 100	$ 126,413
	Total Amount 2010	461,192	$ 950.34	$ 6,124.41	$ 1	$ 427,246
	Amount received from Pfizer 2009	9,892	$ 2,978.78	$ 8,282.64	$ 500	$ 53,605
	Amount received from Pfizer 2010	391,577	$ 318.22	$ 4,148.22	$ 10	$ 427,246
	Amount of payments already disclosed in 2009*	23,563	$ 6,094.07	$ 9,913.76	$ 100	$ 126,413
	Company count 2009	30,222	1.198	0.477	1	4
	Company count 2010	461,192	1.269	0.577	1	7

* At the time Pfizer announced its disclosure, Cephalon, Eli Lilly and GlaxoSmithKline were already disclosing some payments to physicians.

Table 2: Descriptive Statistics

		Mean	St. Dev.	Minimum	Maximum
Physician Characteristics	Female	0.217	0.412	0	1
	Sole Proprietor	0.312	0.463	0	1
	Specialist	0.571	0.495	0	1
Patient characteristics (per physician)	Female	0.550	0.414	0	1
	Inpatient	0.563	0.484	0	1
	Black	0.183	0.324	0	1
	White	0.724	0.379	0	1
	Asian	0.013	0.093	0	1
	HMO as primary payer	0.108	0.249	0	1
	Patient amount due	$ 441.46	$ 6,268.74	$ (14,613)	$ 1,247,471
	Drugs prescribed	0.811	0.302	0	1
	Total Drug Charges	$ 687.93	$ 3,113.96	$ -	$ 279,384
	% of prescriptions branded	0.153	0.298	0	1
	Number of patients seen	2.159	2.526	1	33

Unit of observation is a physician-hospital-diagnosis-month

Table 3: Descriptive Statistics on Dependent Variable

Branded drugs as share of prescriptions

		Observations	Mean	St. Dev	Min	Max
Non-Pfizer	Pre	52,344	0.141	0.289	0	1
	Threat	24,522	0.140	0.290	0	1
	Post	62,280	0.167	0.309	0	1
Pfizer	Pre	494	0.205	0.290	0	1
	Threat	580	0.207	0.280	0	1
	Post	678	0.242	0.296	0	1

Unit of observation is a physician-hospital-diagnosis-month

Each period corresponds to the status of the Pfizer settlement:

Pre: July 2009- December 2009, during which physicians received payments, but Pfizer was not yet required to notify them of disclosure

Threat: January 2010-March 2010, during which physicians know that their names will be disclosed, but disclosure has not yet occurred

Post: April 2010-December 2010, after the publication of the physicians' names on the Pfizer website

Table 4: Characteristics of Physicians

Units: Share of patient visits attributable to each characteristic

	Physicians who received payments from Pfizer in 2009	All other physicians
Female patients	52.5%	55.9%
Inpatients	72.9%	38.3%
Black patients	15.7%	19.2%
White patients	76.5%	66.5%
Asian patients	1.8%	2.7%
HMO is primary payer	17.4%	23.7%

Units: Share of physicians in subsample

Female	6.4%	27.0%
Sole proprietor	25.6%	25.5%
Specialists	70.5%	61.4%

Table 5: Differences-in-Differences Regression Results

Dependent variable: Branded drugs as % prescriptions

		Model 1	Model 2	Model 3	Model 4	Model 5
Payment Status	Pfizer	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
Disclosure Status	Pre-disclosure	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
	Disclosure Threat	-0.004***	-0.007***	-0.007***	-0.005***	-0.004**
		(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
	Disclosure Post	-0.005***	-0.006***	-0.007***	-0.002	-0.002
		(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Effect of Disclosure Status and Payment Status	Pfizer * Pre	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
	Pfizer * Threat	0.001	0.001	0.001	0.001	0.003
		(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
	Pfizer * Post	0.005**	0.005**	0.005**	0.005**	0.006**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Patient Controls	Female patients			0.001	0.001	0.001
				(0.001)	(0.001)	(0.001)
	Black patients			0.008***	0.008***	0.006***
				(0.002)	(0.002)	(0.002)
	White patients			0.007***	0.007***	0.004**
				(0.002)	(0.002)	(0.002)
	Asian patients			0.006	0.006	0.002
				(0.004)	(0.004)	(0.004)
	Patients with HMO as primary payer			-0.003*	-0.003*	-0.002
				(0.001)	(0.001)	(0.002)
	Inpatients			0.053***	0.053***	0.044***
				(0.008)	(0.008)	(0.008)
Fixed Effects	Physician-Hospital FE	Yes	Yes	Yes	Yes	Yes
	Diagnosis FE	Yes	Yes	Yes	Yes	Yes
	Month FE	No	Yes	Yes	Yes	Yes
	Month² * Hospital	No	No	No	Yes	Yes
	Weighted by patient volumes	No	No	No	No	Yes
	Constant	0.160***	0.161***	0.122***	0.120***	0.125***
		(0.004)	(0.004)	(0.006)	(0.006)	(0.005)
	R-squared	0.855	0.855	0.856	0.856	0.876
	N	140,576	140,576	140,576	140,576	140,576

* p<.1, ** p<.05, *** p<.01

Standard errors are robust and clustered at the doctor-hospital level.

Table 6: Effect of Future Payments from Pfizer Not Yet Disclosed				
Dependent variable: Branded drugs as % prescriptions				
		Model 3	Model 4	Model 5
Payment Status	Pfizer 2009 Only	Absorbed	Absorbed	Absorbed
	Pfizer 2010	Absorbed	Absorbed	Absorbed
Disclosure Status	Pre	Absorbed	Absorbed	Absorbed
	Threat	-0.007***	-0.005**	-0.004**
		(0.002)	(0.002)	(0.002)
	Post	-0.007***	-0.002	-0.002
		(0.002)	(0.002)	(0.002)
Effect of disclosure status and payment status	Pfizer 2009 * Pre	Absorbed	Absorbed	Absorbed
	Pfizer 2009 * Threat	0.001	0.001	0.003
		(0.004)	(0.004)	(0.007)
	Pfizer 2009 * Post	0.005**	0.005**	0.006**
		(0.002)	(0.002)	(0.003)
	Pfizer 2010 * Pre	Absorbed	Absorbed	Absorbed
	Pfizer 2010 * Threat	-0.000	-0.001	-0.000
		(0.002)	(0.002)	(0.002)
	Pfizer 2010 * Post	0.000	0.000	0.001
		(0.002)	(0.002)	(0.002)
Patient Controls	Female patients	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
	Black patients	0.008***	0.008***	0.006***
		(0.002)	(0.002)	(0.002)
	White patients	0.007***	0.007***	0.004**
		(0.002)	(0.002)	(0.002)
	Asian patients	0.006	0.006	0.002
		(0.004)	(0.004)	(0.004)
	Patients with HMO as primary payer	-0.003*	-0.003*	-0.002
		(0.001)	(0.001)	(0.002)
	Inpatients	0.053***	0.053***	0.044***
		(0.008)	(0.008)	(0.008)
Fixed Effects	Physician-Hospital FE	Yes	Yes	Yes
	Diagnosis FE	Yes	Yes	Yes
	Month FE	Yes	Yes	Yes
	$Month^2$ * Hospital	No	Yes	Yes
	Weighted by patient volumes	No	No	Yes
	Constant	0.122***	0.120***	0.125***
		(0.006)	(0.006)	(0.005)
	R-squared	0.856	0.856	0.876
	N	140,576	140,575	140,576
	* p<.1, ** p<.05, *** p<.01			
	Standard errors are robust and clustered at the doctor-hospital level.			

Table 7: Effect of Future Payments Not Yet Disclosed (From Any Company)

Dependent variable: Branded drugs as % prescriptions

		Model 3	Model 4	Model 5
Payment status	Pfizer 2009	Absorbed	Absorbed	Absorbed
	Pfizer 2010 Only	Absorbed	Absorbed	Absorbed
	Other 2010 Payment	Absorbed	Absorbed	Absorbed
Disclosure Status	Pre	Absorbed	Absorbed	Absorbed
	Threat	-0.007***	-0.005**	-0.004**
		(0.002)	(0.002)	(0.002)
	Post	-0.007***	-0.002	-0.002
		(0.002)	(0.002)	(0.002)
Effect of disclosure status and payment status	Pfizer 2009 * Pre	Absorbed	Absorbed	Absorbed
	Pfizer 2009 * Threat	0.001	0.001	0.003
		(0.004)	(0.004)	(0.007)
	Pfizer 2009 * Post	0.005**	0.005**	0.006**
		(0.002)	(0.002)	(0.003)
	Pfizer 2010 * Pre	Absorbed	Absorbed	Absorbed
	Pfizer 2010 * Threat	0.001	0.000	0.001
		(0.002)	(0.002)	(0.002)
	Pfizer 2010 * Post	0.002	0.002	0.003
		(0.002)	(0.002)	(0.002)
	Other 2010 * Pre	Absorbed	Absorbed	Absorbed
	Other 2010 * Threat	-0.002	-0.001	-0.001
		(0.003)	(0.003)	(0.003)
	Other 2010 * Post	-0.004	-0.004	-0.003
		(0.004)	(0.004)	(0.004)
Patient Controls	Female patients	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
	Black patients	0.008***	0.008***	0.006***
		(0.002)	(0.002)	(0.002)
	White patients	0.007***	0.007***	0.005**
		(0.002)	(0.002)	(0.002)
	Asian patients	0.006	0.006	0.002
		(0.004)	(0.004)	(0.004)
	Patients with HMO as primary payer	-0.003*	-0.003*	-0.002
		(0.001)	(0.001)	(0.002)
	Inpatients	0.053***	0.053***	0.044***
		(0.008)	(0.008)	(0.008)
Fixed Effects	Physician-Hospital FE	Yes	Yes	Yes
	Diagnosis FE	Yes	Yes	Yes
	Month FE	Yes	Yes	Yes
	$Month^2$ * Hospital	No	Yes	Yes
	Weighted by patient volumes	No	No	Yes
	Constant	0.122***	0.120***	0.125***
		(0.006)	(0.006)	(0.005)
	R-squared	0.856	0.856	0.876
	N	140,574	140,575	140,576
	* p<.1, ** p<.05, *** p<.01			
	Standard errors are robust and clustered at the doctor-hospital level.			

Table 8: Effect of non-Pfizer Payments Already Disclosed in 2009

Dependent variable: Branded drugs as % prescriptions

		Model 3	Model 4	Model 5
Payment Status	Pfizer 2009 Only	Absorbed	Absorbed	Absorbed
	Pfizer 2009 & Other 2009 payments	Absorbed	Absorbed	Absorbed
Disclosure Status	Pre	Absorbed	Absorbed	Absorbed
	Threat	-0.007***	-0.005***	-0.004**
		(0.002)	(0.002)	(0.002)
	Post	-0.007***	-0.002	-0.002
		(0.002)	(0.002)	(0.002)
Effect of disclosure status and payment status	Pfizer 2009 Only * Pre	Absorbed	Absorbed	Absorbed
	Pfizer 2009 Only * Threat	-0.003	-0.004	-0.005
		(0.006)	(0.006)	(0.007)
	Pfizer 2009 Only * Post	0.003*	0.003*	0.003**
		(0.002)	(0.002)	(0.001)
	Pfizer 2009 & Others * Pre	Absorbed	Absorbed	Absorbed
	Pfizer 2009 & Others * Threat	0.004	0.004	0.011
		(0.005)	(0.005)	(0.012)
	Pfizer 2009 & Others * Post	0.006**	0.006**	0.010**
		(0.003)	(0.003)	(0.004)
Patient Controls	Female patients	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
	Black patients	0.008***	0.008***	0.006***
		(0.002)	(0.002)	(0.002)
	White patients	0.007***	0.007***	0.005**
		(0.002)	(0.002)	(0.002)
	Asian patients	0.006	0.006	0.002
		(0.004)	(0.004)	(0.004)
	Patients with HMO as primary payer	-0.003*	-0.003*	-0.002
		(0.001)	(0.001)	(0.002)
	Inpatients	0.053***	0.053***	0.044***
		(0.008)	(0.008)	(0.008)
Fixed Effects	Physician-Hospital FE	Yes	Yes	Yes
	Diagnosis FE	Yes	Yes	Yes
	Month FE	Yes	Yes	Yes
	Month² * Hospital	No	Yes	Yes
	Weighted by patient volumes	No	No	Yes
	Constant	0.122***	0.120***	0.125***
		(0.006)	(0.006)	(0.005)
	R-squared	0.856	0.856	0.876
	N	140,576	140,575	140,576
	* p<.1, ** p<.05, *** p<.01			
	Standard errors are robust and clustered at the doctor-hospital level.			

Appendix: Effect of Other Communications About Disclosure

Dependent variable: Branded drugs as % prescriptions

		4 Month Post Period		2 Month Post Period		1 Month Post Period	
Payment Status	Pfizer	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
Pfizer Press Release	Post February 9th	-0.001		0.002		-0.000	
		(0.002)		(0.002)		(0.002)	
	Pfizer * Post	-0.009		-0.009		-0.017	
		(0.009)		(0.008)		(0.016)	
New York Times Article	Post NY Times Article		0.001		0.000		0.001
			(0.002)		(0.002)		(0.002)
	Pfizer * Post		-0.017		-0.012		-0.007
			(0.013)		(0.010)		(0.013)
Patient Controls	Female patients	0.001	0.001	0.002	-0.000	-0.000	0.001
		(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
	Black patients	0.005*	0.007**	0.006	0.006	0.011*	0.004
		(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.006)
	White patients	0.005**	0.008***	0.006	0.008**	0.006	0.006
		(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
	Asian patients	0.009	0.010*	0.002	-0.000	0.001	0.007
		(0.005)	(0.005)	(0.007)	(0.007)	(0.009)	(0.012)
	Patients with HMO as primary payer	-0.007***	-0.007***	-0.005**	-0.005**	-0.005	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
	Inpatients	0.034***	0.041***	0.037***	0.040***	0.031***	0.044***
		(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.010)
Fixed Effects	Weighted by patient volumes	Yes	Yes	Yes	Yes	Yes	Yes
	Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes
	Month FE	Yes	Yes	Yes	Yes	Yes	Yes
	Physician-hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
	Constant	0.111***	0.116***	0.102***	0.120***	0.096***	0.125***
		(0.006)	(0.007)	(0.007)	(0.008)	(0.009)	(0.012)
	R-squared	0.885	0.869	0.900	0.876	0.903	0.880
	N	75,838	76,269	38,087	38,196	18,658	18,802

* p<.1, ** p<.05, *** p<.01

Standard errors are robust and clustered at the doctor-hospital level.

REFERENCES

American Medical Association. “Interactions with Pharmaceutical Industry Representatives.” http://www.ama-assn.org/ama/pub/physician-resources/legal-topics/business-management-topics/interactions-pharmaceutical-industry-representatives.page.

Anon. 2011. “Doctors Often Receive Payments From Drug Companies : NPR.” *Talk of the Nation*. National Public Radio. http://www.npr.org/2011/09/13/140438636/doctors-often-receive-payments-from-drug-companies.

———. “Med Schools Flunk at Keeping Faculty Off Pharma Speaking Circuit - ProPublica.” *ProPublica*. http://www.propublica.org/article/medical-schools-policies-on-faculty-and-drug-company-speaking-circuit.

———. “Medicare, Medicaid, Children’s Health Insurance Programs; Transparency Reports and Reporting of Physician Ownership or Investment Interests.” http://www.gpo.gov/fdsys/pkg/FR-2011-12-19/pdf/2011-32244.pdf.

———. “About the Dollars for Docs Data.” *ProPublica*. http://www.propublica.org/article/about-our-pharma-data.

ASPA. “Justice Department Announces Largest Health Care Fraud Settlement in Its History.” http://www.hhs.gov/news/press/2009pres/09/20090902a.html.

Bar-Isaac, Heski, and Joyee Deb. 2012. . http://pages.stern.nyu.edu/~hbar-isa/RS2M.pdf.

Boudreau, John W. (1991). Utility analysis for decisions in human resource management. In Marvin D. Dunnette & Leatta M. Hough (Eds.) Handbook of Industrial and Organizational Psychology, (2nd ed.), Vol. 2. Palo Alto: Consulting Psychologists Press, pp. 621-745

Bush, Haydn. 2012. “Hospital Statistics Chart Rise in Physician Employment.” *Hospitals and Health Networks Daily*. http://www.hhnmag.com/hhnmag/HHNDaily/HHNDailyDisplay.dhtml?id=1970001363.

Cain, Daylian M., George Loewenstein, and Don A. Moore. 2005. “The Dirt on Coming Clean: Perverse Effects of Disclosing Conflicts of Interest.” *The Journal of Legal Studies* 34 (1) (January 1): 1–25.

Chatterji, Aaron K., Kira R. Fabrizio, Will Mitchell, and Kevin A. Schulman. 2008. “Physician-Industry Cooperation In The Medical Device Industry.” *Health Affairs* 27 (6) (November 1): 1532–1543. doi:10.1377/hlthaff.27.6.1532.

Chugh, Dolly, Max H. Bazerman, and Mahzarin R. Banaji. 2005. “Bounded Ethicality as a Psychological Barrier to Recognizing Conflicts of Interest.” In *Conflicts of Interest: Challenges and Solutions in Business, Law, Medicine, and Public Policy*, ed. D. A. Moore, D. M. Cain, G. Loewenstein, and M. H. Bazerman, 74–95. New York, NY, US: Cambridge University Press.

Cranston, Ross F. 1979. “Regulating Conflict of Interest of Public Officials: A Comparative Analysis.” *Vanderbilt Journal of Transnational Law* 12: 215.

Dana, J., and G. Loewenstein. 2003. “A Social Science Perspective on Gifts to Physicians From Industry.” *JAMA: The Journal of the American Medical Association* 290 (2) (July 9): 252–255. doi:10.1001/jama.290.2.252.

Emanuel, E. J., and A. S. Brett. “MANAGED COMPETITION AND THE PATIENT-PHYSICIAN RELATIONSHIP.” *The New England journal of medicine* 329 (12): 879–882.

Fugh-Berman, Adriane. 2008. “Prescription Tracking and Public Health.” *Journal of General Internal Medicine* 23 (8) (August): 1277–1280. doi:10.1007/s11606-008-0630-0.

Gibbons, Robert V., Frank J. Landry, Denise L. Blouch, David L. Jones, Frederick K. Williams, Catherine R. Lucey, and Kurt Kroenke. 1998. “A Comparison of Physicians’ and Patients’ Attitudes Toward Pharmaceutical Industry Gifts.” *Journal of General Internal Medicine* 13 (3): 151–154. doi:10.1046/j.1525-1497.1998.00048.x.

Goes, J B, and C Zhan. 1995. “The Effects of Hospital-physician Integration Strategies on Hospital Financial Performance.” *Health Services Research* 30 (4) (October): 507–530.

Gonzalez, Jorge, Catarina Sismeiro, Shantanu Dutta, and Philip Stern. 2008. “Can Branded Drugs Benefit from Generic Entry? The Role of Detailing and Price in Switching to Non-bioequivalent Molecules.” *International Journal of Research in Marketing* 25 (4) (December): 247–260. doi:10.1016/j.ijresmar.2008.08.002.

Hall, Mark A. 1988. “Institutional Control of Physician Behavior: Legal Barriers to Health Care Cost Containment.” *University of Pennsylvania Law Review* 137 (2) (December 1): 431–536. doi:10.2307/3312252.

Hart, Oliver D., and Jean Tirole. 1990. “Verticle Integration and Market Foreclosure.” http://dspace.mit.edu/handle/1721.1/50143.

Heckman, James J., Hidehiko Ichimura, and Petra E. Todd. 1997. “Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme.” *The Review of Economic Studies* 64 (4) (October 1): 605–654. doi:10.2307/2971733.

Hellerstein, Judith K. 1998. “The Importance of the Physician in the Generic Versus Trade-Name Prescription Decision.” *The RAND Journal of Economics* 29 (1) (April 1): 108–136. doi:10.2307/2555818.

HHS Press Release. 2009. “Justice Department Announces Largest Health Care Fraud Settlement in Its History.” http://www.hhs.gov/news/press/2009pres/09/20090902a.html.

Jastifer, James, and Sarah Roberts. 2009. “Patients’ Awareness of and Attitudes Toward Gifts from Pharmaceutical Companies to Physicians.” *International Journal of Health Services: Planning, Administration, Evaluation* 39 (2): 405–414.

Jensen, Gail A., and Michael A. Morrisey. 1986. “The Role of Physicians in Hospital Production.” *The Review of Economics and Statistics* 68 (3) (August 1): 432–442. doi:10.2307/1926020.

Kong, Ying, and James R. Seldon. 2004. “Pseudo-Generic Products and Barriers to Entry in Pharmaceutical Markets.” *Review of Industrial Organization* 25 (1): 71–86. doi:10.1023/B:REIO.0000040524.32034.04.

Kube, Sebastian, Michel André Maréchal, and Clemens Puppe. 2010. *The Currency of Reciprocity - Gift-exchange in the Workplace*. IEW - Working Paper. Institute for Empirical Research in Economics - University of Zurich. http://ideas.repec.org/p/zur/iewwpx/377.html.

Loewenstein, George, Sunita Sah, and Daylian M. Cain. 2012. “The Unintended Consequences of Conflict of Interest Disclosure.” *JAMA: The Journal of the American Medical Association* 307 (7) (February 15): 669. doi:10.1001/jama.2012.154.

Mechanic D. 2003. “Physician Discontent: Challenges and Opportunities.” *JAMA: The Journal of the American Medical Association* 290 (7) (August 20): 941–946. doi:10.1001/jama.290.7.941.

Melo-Martín, Inmaculada de, and Kristen Intemann. 2009. “How Do Disclosure Policies Fail? Let Us Count the Ways.” *The FASEB Journal* 23 (6) (June 1): 1638–1642. doi:10.1096/fj.08-125963.

Moore, Don A., Daylian M. Cain, George Loewenstein, and Max H. Bazerman. 2005. *Conflicts of Interest: Challenges and Solutions in Business, Law, Medicine, and Public Policy*. Cambridge University Press.

Mullen, Kathleen J., Richard G. Frank, and Meredith B. Rosenthal. 2010. “Can You Get What You Pay for? Pay-for-performance and the Quality of Healthcare Providers.” *The RAND Journal of Economics* 41 (1): 64–91. doi:10.1111/j.1756-2171.2009.00090.x.

Pham-Kanter G, Alexander G. 2012. “EFfect of Physician Payment Disclosure Laws on Prescribing.” *Archives of Internal Medicine* 172 (10) (May 28): 819–821. doi:10.1001/archinternmed.2012.1210.

Posner, Karen L., William M. Gild, and Edgar V. Winans. 1995. “Changes in Clinical Practice in Response to Reductions in Reimbursement: Physician Autonomy and Resistance to Bureaucratization.” *Medical Anthropology Quarterly* 9 (4): 476–492. doi:10.1525/maq.1995.9.4.02a00040.

Rechner, Paula L., and Dan R. Dalton. 1991. “CEO Duality and Organizational Performance: A Longitudinal Analysis.” *Strategic Management Journal* 12 (2): 155–160. doi:10.1002/smj.4250120206.

Rosenthal, Meredith B., Richard G. Frank, Joan L. Buchanan, and Arnold M. Epstein. 2002. “Transmission Of Financial Incentives To Physicians By Intermediary Organizations In California.” *Health Affairs* 21 (4) (July 1): 197–205. doi:10.1377/hlthaff.21.4.197.

Ross, J. S., J. E. Lackner, P. Lurie, C. P. Gross, S. Wolfe, and H. M. Krumholz. 2007. "Pharmaceutical Company Payments to Physicians: Early Experiences With Disclosure Laws in Vermont and Minnesota." *JAMA: The Journal of the American Medical Association* 297 (11) (March 21): 1216–1223. doi:10.1001/jama.297.11.1216.

Safran, D G, J E Montgomery, H Chang, J Murphy, and W H Rogers. 2001. "Switching Doctors: Predictors of Voluntary Disenrollment from a Primary Physician's Practice." *The Journal of Family Practice* 50 (2) (February): 130–136.

Segal, Ilya. 1999. "Contracting with Externalities." *The Quarterly Journal of Economics* 114 (2) (May 1): 337–388. doi:10.1162/003355399556016.

Snyder, Jason. 2010. "Gaming the Liver Transplant Market." *Journal of Law, Economics, and Organization* 26 (3) (December 1): 546–568. doi:10.1093/jleo/ewq003.

Steinbrook, Robert. 2012. "'Transparency Reports' on Industry Payments to Physicians and Teaching Hospitals." *JAMA: The Journal of the American Medical Association* 307 (10) (March 14): 1029. doi:10.1001/jama.2012.211.

CHAPTER 3: THE PERSUASIVE EFFECT OF EXTERNAL FINANCIAL INCENTIVES

THE INFLUENCE OF PHARMACEUTICAL INDUSTRY PAYMENTS ON PHYSICIAN CHOICE

I. INTRODUCTION

The potential for conflict of interest between the owners and managers of a firm is one of the fundamental issues in strategy, and one that has preoccupied scholars for many years. More recently, external financial relationships have drawn increasing scrutiny as a potential source of conflict between managers and owners. Doubtless much of this scrutiny is due to a proliferation of cases in which the financial conflicts of management have had hugely detrimental effects on the performance of their firms.

Examining such extreme cases in retrospect, the evidence of corruption is often painfully obvious. Yet most of the conflicts of interest that firms must deal with are more insidious because they are less obvious, and thereby have been allowed to proliferate (Simon, 1983). What differentiates these “everyday conflicts” from egregious corruption is the potential for the firm to benefit as well. One example of such is a CEO who holds an outside directorship; there is evidence of the benefits which accrue to CEOs for serving as directors on the boards of other firms (Yermack, 2004) and doing so destroys firm value (Rosenstein and Wyatt, 1994), which naturally suggests a conflict of interest. Other research, however, has indicated the potential benefit that having a CEO on an outside board might remit to the firm, particularly learning (Geletkanycz and Hambrick, 1997). In the presence of a potential benefit to the firm as well as the CEO, it becomes much more difficult for a firm to say with certainty what constitutes a conflict of interest.

While external financial relationships of the top management team have received increasing scrutiny, there has not been comparable attention paid to managers and decision-makers outside the C-suite. This is problematic for two reasons: first, while non-executive employees are certainly less visible and at an individual level have less of an impact on firm performance, at an aggregate level the decisions made within the firm are crucial for firm performance (Woolridge and Floyd, 1990). Secondly, the nature of the conflicts of interest faced by non-executives is distinct. The crucial question—whether an external financial relationship exerts a *negative* influence on a given manager—is the same, and remains difficult to identify. These incentives are provided to them because it would allow another firm (generally a supplier) to capture value from their firm. At the same time, it is crucial for managers to have at least some contact with these outside firms in order to properly evaluate their choices. This gives rise to a simple question that is quite difficult to answer: was the employee's action due to the persuasion created by this external incentive, or would they have made the same choice regardless? How does one differentiate the beneficial influence of learning from the negative influence of persuasion or obligation?

As with executives, evaluating whether potentially beneficial relationships exert a detrimental effect on workers is very difficult to test; it requires decisions to be repeated and comparable over time, and for researchers to be able to observe changes in external financial relationships in order to assess the counterfactual. I will circumvent these obstacles by examining the effect of financial relationships between physicians and pharmaceutical companies, and their effect on prescribing behavior. To address the problem of discerning negative influence, I will look at the effect of withdrawing payments unrelated to a change in product offerings—thus any changes will be due to the (absence of) the persuasive power of payments from pharmaceutical companies. The well-codified nature of medical diagnoses will allow me to compare a given decision-maker (in this case, a physician) over time and ensure the comparability of his decisions. This paper makes a significant contribution to understanding the persuasive impact of external financial relationships within the medical industry specifically, as well as provides insights for firms facing similar problems more generally.

I find that following the removal of payments, physicians significantly alter their prescribing behavior; in particular, this behavior is consistent with learning by doing. Physicians who have had their payments cut off increase their prescriptions of drugs—both branded and generic—consistent with evidence that physicians with more experience have more concentrated prescribing behavior. Introducing a shock to their preferences by removing the persuasive payment seems to induce them to experiment with and thereby learn about alternative treatments for the same types of diagnoses. The idea that removing an external financial incentive induces greater effort to independent learning may have serious implications for performance.

This paper proceeds as follows: Section 2 presents the background for this question, and develops propositions on how removing payments will influence physician behavior. Section 3 provides details on the medical care setting and the data used to address the question, and Section 4 details the resultant estimation strategy. Section 5 discusses the results, and Section 6 concludes and discusses avenues for future research.

II. Background and Hypothesis Development

It has been established often and well that perverse incentives can undermine the behavior of employees. While more popular attention has been paid to the types of conflicts of interest that can cause a 100 billion dollar company to implode (rather than choosing a specific citation, anyone in need of evidence of this may simply type “Enron” into Google), the strategy literature is often concerned with the types of conflicts of interest that can plague even uncorrupt firms. One well-studied example is firm executives holding outside directorships. It has been well documented that although executives accrue both financial and personal gains from such positions (Yermack, 2004), such relationships may be detrimental to the performance of their firms (Rosenstein and Wyatt, 1994). These relationships are not typically referred to as conflicts of interest, however, because there is plenty of evidence to suggest that this type of external financial relationship is not uniformly detrimental to the CEO’s firm, and may result in performance-enhancing learning (Geletkanycz and Hambrick, 1997; Haunschild, 1993).

Although strategy research has recently been disproportionately concerned with agency issues in the C-suite (Larkin, Pierce, and Gino, 2012), such opportunities for outside relationships certainly exist for middle managers as well. One obvious example is procurement contracts (Handfield and Baumer, 2006; Carter, 2000). Annual expenditures on business gifts were estimated to be $1.5 billion in 1989, or the equivalent of $2.8 billion in 2013, assuming no growth whatsoever (Dorsch and Kelley, 1994), and one in 8 companies in a private survey reported that they had experienced vendor, supplier or procurement fraud in the last year (Kroll Advisory—Proving Staff Kickback Allegations).While most companies have policies forbidding explicit bribes, many other questionable behaviors such as accepting gifts or favors from suppliers (Cooper, Frank and Kemp, 1997) or showing supplier favoritism based on a family connection (Handfield and Baumer, 2006) are not technically forbidden. Most companies rely on a generalized code of ethics; however, given the nature of a procurement manager's repeated interactions with suppliers, it would be difficult if not impossible for a firm to forbid contracts with any company that had worked to develop a positive relationship with the manager.

From the CEO to middle manager, whether the firm should go beyond cultivating ethical norms to intervene in these types of outside relationships depends on a) how much intervention costs, and b) whether the behavior in question is actually hurting the firm. As MacCoun (in Moore et al, 2005) notes, clear and inexpensive solutions to conflicts of interest are quite rare; monitoring is costly, and even inducing employee whistle-blowing may be difficult in cases where the ethicality is unclear. The firm may then resort to outright prohibition of any type of financial relationship—but then the potential learning benefits will be lost as well. Firms are really only concerned with external financial relationships to the extent that they exert a *negative* influence on their workers. When conflicts of interest may (at least ostensibly) be linked to beneficial behaviors as well, the argument in their favor becomes much more convincing and much more difficult to disentangle. To return to the example of the procurement manager, it may actually be true that the best contract was offered by the vendor that happened to offer product training at a resort in Hawaii. Many employees and professionals express the opinion that there is no harm in accepting payments from a company whose services or product they would have used anyway (Vogt, 2011; Handfield and Baumer, 2006).

The crucial question in these outside financial relationships, then, is similar to one of the central questions in marketing: is the effect informative or persuasive (Leffler, 1981)? To the extent that financial relationships can be said to fall into one or the other category makes the ethicality much more clear. Take a hypothetical example of a procurement manager. If suppliers pay to fly him out to view their factory so that he may become more informed about their product, this is clearly beneficial for his firm. If, instead, suppliers pay to fly him to a vacation destination which in turn persuades him to accept their contract, this is detrimental. In fact, services or payments with the intent to persuade (without information) are, by definition, bribes. In reality, most people will reject such situations that are openly corrupt (Chugh et al in Moore et al, 2005). Instead, it is because most external financial arrangements fall in between these two poles that it may be difficult for individual workers to even identify what constitutes a conflict of interest (Ibid.; Gino and Bazerman, 2009).

Clearly there is an extensive literature in marketing on estimating persuasive versus informational effects in advertising. And given the pervasiveness of outside financial relationships in organizations (Moore et al, 2006), it may at first be surprising that similar estimations have not also been undertaken for outside financial relationships. Organizational decisions and external financial relationships, in contrast with advertising, are difficult to observe and identify. Firstly, most external financial relationships are not reported if they are not illegal (Cooper, Frank and Kemp, 1997). CEO outside directorships are one of the few counter-examples to this, which is perhaps why they have received so much academic attention compared to non-C-suite decision-makers. Secondly, while product choices are observable and the choice set is fairly quantifiable, the same cannot be said for decisions made across organizations. The lack of comparability across decisions, even within a single firm, makes panel analysis difficult even if data were available. Cross-sectional analysis is even more difficult, given that decision-makers with external financial relationships may (legitimately) differ systematically from those without. One of the most common explanations given for accepting gifts vendors is “I would not have accepted the gift if I were not going to use their product anyway." Thus simple comparisons across decision-makers who have external financial relationships may just reflect underlying preferences that would be expressed even in the absence of payments.

In order to resolve these issues and ascertain the presence of a non-informational effect of external financial relationships on decision-making, I will address this question using data from pharmaceutical industry payments to physicians practicing in hospitals. This setting resolves a number of the issues that have prevented researchers from addressing this question in the past. First and foremost is the observability of payments, even when they are not illegal. As of this writing, 15 pharmaceutical companies accounting for 47% of total market share are disclosing payments or benefits in-kind that they have given to physicians. These payments encompass a large swath of perquisites, most of which can be found in other industries as well, such as travel to conferences, meals, and consulting arrangements. Also included are speaking fees—fees paid to physicians to give presentations to audiences of other physicians, typically informing them about the benefits of the company's drugs.[31] These payments help to address the observability of (at least technically) legal payments. Furthermore, the medical industry provides a unique setting in which one can observe individual decisions made within an organization (in this case, by a physician within a hospital). Each of these decisions can further be categorized and evaluated using nationally standardized classifications for disease, acuity, and characteristics of each doctor's patient that may affect his decisions. Thus, the medical setting provides a unique ability to compare decisions over time that is crucial to this type of question.

[31] Speakers may be paid to present research that may not explicitly promote a particular product. The informational versus persuasive value of these presentations are by no means agreed upon. See http://www.propublica.org/article/with-our-dollars-for-docs-update-coming-drug-companies-defend-interactions for a discussion.

The difficulty of estimating whether these payments have a persuasive effect, separate from their informational value, is particularly problematic in the health care industry, where, as one physician observed "a lot of what you learn about products is from people that sell the products… You have to learn it somewhere."[32] If a physician receives a payment for consulting that enables the development of a superior product, this creates value for the physician, the pharmaceutical company, and the patient (Chatterji et al, 2008). Similarly, if a physician is paid to present research about a superior pharmaceutical treatment, it may very well be clinically, socially, and economically beneficial for all involved if he prescribes this treatment to his patients, regardless of the payment he received. Indeed, many physicians who speak on behalf of pharmaceutical companies assert that they would never present content that they did not believe was scientifically sound, and they believed their talks were purely educational (ProPublica.org, "Med Schools Flunk at Keeping Faculty Off Pharma Speaking Circuit").

Figure 1 illustrates this problem by looking at the change in prescribing behavior by physicians who received a new payment from a pharmaceutical company. The figure compares the year-over-year change in prescribing behavior by physicians who received payments from the pharmaceutical manufacturer GlaxoSmithKline in 2009 and 2010 versus only in 2010, relative to all other physicians. Clearly, the introduction of a *new* payment affects physician prescribing behavior, while physicians who had been receiving payments were not statistically discernible from other physicians—is this because of a change in attitudes toward GSK drugs due to persuasion? Or did these physicians learn valuable

[32] http://www.propublica.org/article/heart-docs-reject-claims-of-bias-from-industry-money

information from their contact with the company? As discussed before, the answer is likely "both."

To resolve this issue, in this paper I will examine the effect of removing payments on physicians' prescribing behavior. It is possible that ceasing payments may also coincide with physician learning in this setting: pharmaceutical companies pay significantly less (if at all) to promote products which have gone off patent (Berndt, Kyle and Ling, 2003). Thus, suspension of payments could coincide with learning about a generic alternative. I will, then, look at a specific case in which physicians were "laid off." Between 2009 and 2010, GlaxoSmithKline (GSK) reduced their quarterly payments to physicians by 15 percent. GSK spokeswoman Mary Anne Rhyne communicated the company's intention to ultimately cut the number of physicians paid to speak on their behalf by 50 percent, citing that it would be "a better use of resources to use fewer speakers more often." This decision to reduce their payments by continuing to pay some physicians, while withdrawing payments from others, will allow me to examine the effect of withdrawing payment independent of changes in their product line, thus eliminating potential informational effects on physician behavior.

While I am unable to find any literature quantifying the impact of *removing* a conflict of interest per se, such payments are largely analogous to both advertising and more traditional payments such as salaries. The advertising literature demonstrates that in a competitive market, sustained advertising is necessary to maintain an effect from persuasive advertising (Hanssens, 2011). In terms of explicit monetary incentives, Kube, Marechal and Puppe (2011) demonstrate that reducing wages below what workers had expected reduced their productivity in a way that suggested reciprocity.

Proposition 1: Reducing pharmaceutical payments to physicians will alter their prescribing behavior.

This does not address, however, workers' expectations of future payments. Because these external financial relationships cannot be explicitly quid pro quo, payments may fluctuate from year to year. Thus a reduction may reasonably be viewed as temporary, versus a payment that is cut off entirely. There is very little extant research on such a situation, because it is one that is essentially unique to a conflict of interest relationship, and the effect of removing conflicts is not well studied. In a traditional setting, there is no reason whatsoever for a worker to continue working after he is no longer being paid. In the conflict of interest setting, however, because explicit pay-for-performance is illegal (and may be more reasonably called a bribe or a kickback), it is very possible that an individual who no longer receives the payment may carry on as before. Simplistically, it seems reasonable to assume that a physician who has had his payment reduced will have a greater expectation of future payments than a physician who has had his payments cut entirely. The expectation of future payments may provide incentives for these physicians to remain more "loyal" to the pharmaceutical company. This leads to:

Proposition 2: Cutting payments to physicians will have a greater impact than reducing payments on physician prescribing behavior.

Notably, neither of these propositions specify the way in which physicians will alter their prescribing behavior, because there are a number of potential directions in which physicians' behavior may change. While there are many different potential dimensions along which a physician's prescribing behavior might change, with a multitude of explanations, I present the here the two with the most support in theoretical, empirical or popular literature:

Inappropriate prescription: if, when an external industry payment is removed, the physician prescribes fewer drugs, rather than substituting to different drugs, then this suggests that the payment induced the physician to overprescribe. This has been alleged quite frequently in the popular press (e.g., Meier, 2012; Lipton and Sack, 2013) as well as in medical care literature (e.g., Semin, 2000; Smith et al, 2006). In this case, we would expected the physician's branded prescriptions to decline, (both in absolute terms and as a share of his total prescriptions), as well as the share of his patients who are prescribed branded drugs.

Learning: there is a large literature to support the idea that physicians learn by doing (see Ramanarayanan, 2008 for a review) and prescription practices are no different. Taub et al (2011) demonstrate that training and years of experience are substitutes in the concentration of physician's prescribing behavior. That is, prescribers with more experience tend to concentrate their prescriptions among a smaller number of drugs, consistent with the idea that physicians learn about their prescribing preferences through writing actual prescriptions. Thus, over time, physicians become more concentrated prescribers.

This suggests that in the face of a shock to the physician's preferences—where they previously may have concentrated much of their prescriptions on a particular drug which they no longer have a strong preference for—he will have to learn about different products in order to substitute effectively for his patients. In this case, we would expect physicians to increase the number of both branded and generic prescriptions written, and potentially the share of patients as well as they learn and experiment with appropriate applications of less familiar treatments.

The learning hypothesis will also be affected by payments from other pharmaceutical companies that the physician receives. Doctors who receive payments from multiple companies will be more likely to substitute within the product ranges of the companies for whom they are still being paid. Therefore, the learning behavior of physicians who have been cut off entirely will be more diffuse. This leads to:

Proposition 3: physicians who have had their payments cut but are still receiving payments from other companies will be significantly different from physicians who have had their payments cut but are not receiving other payments.

In order to examine these propositions, I will use the data described in the section that follows.

III. Data and Setting

GlaxoSmithKline began voluntarily disclosing payments greater than $300 to physicians for speaking fees and consulting (excluding research) in 2009. Later, these disclosures became compulsory after GSK settled with the U.S. Department of Justice for inappropriate promotion of their drugs. In July 2012, GSK agreed to settle an investigation by the U.S. Department of Justice (DOJ), including the largest fine ($3 billion) in the history of healthcare fraud in the U.S. As part of the investigation, GSK was found guilty of paying explicit kickbacks to physicians. According to one of the attorneys representing the DOJ, "the sales force bribed physicians to prescribe GSK products using every imaginable form of high-priced entertainment, from Hawaiian vacations [and] paying doctors millions of dollars to go on speaking tours, to tickets to Madonna concerts."[33] The dates of the alleged kickbacks are from 1998 to 2005. Given that GSK was already under investigation by the DOJ as of 2009, it

[33] "GlaxoSmithKline to pay $3bn in US drug fraud scandal": http://www.bbc.co.uk/news/world-us-canada-18673220

is unlikely that the payments examined here are representative of such overtly corrupt practices. However, it is also worth noting that unlike many companies who were required to disclose, the voluntary disclosures in 2009 and 2010 exclude payments in kind for travel, meals, or gifts.

In 2009 and 2010, GSK disclosed payments ranging from $300 to $123,900 for consulting and speaking to physicians in the state of New Jersey. The specifics of these payments are taken from propublica.org. ProPublica is a Pulitzer-prize winning non-profit investigative organization that has aggregated the information on payments to physicians published by individual pharmaceutical companies (http://www.propublica.org/series/dollars-for-docs). In the interest of genuine transparency and ease of patient access, ProPublica has aggregated the data published by all pharmaceutical companies currently reporting payments. These firms accounted for 47 percent of revenues in the pharmaceutical industry as of 2012 ("About the Dollars for Docs Data," ProPublica, 2012).[34]

In order to test the effect of the disclosure of payments on physician prescribing behavior, I have matched combined the data on payments with data provided by the New Jersey Department of Health and Senior Services UB-92 dataset, which records all patient discharges from hospitals in New Jersey, for the years 2009-2010. [35] Detailed information is collected for each discharge, including the identifier of the attending physician; the charges for the visit, including itemized breakdown of charges associated with different services; a detailed breakdown of payment, including health plans that provided coverage, the total amount paid (rather than what was initially billed), the patient's contribution, and so forth;

[34] http://www.propublica.org/article/about-our-pharma-data

[35] Excluding psychiatric hospitals.

patient demographics; and all diagnoses recorded during a given visit, as well as procedures. In this setting I am particularly interested in charges for prescription drugs. The two principal limitations of these data are the absence of specific brand names and prescriptions written by physicians that patients fill themselves at a pharmacy. The only drug charges recorded in these data are for those drugs that are administered to the patient while in the hospital, and they are indicated as either branded or generic, without additional specifics. It should be noted that in-hospital prescriptions significantly understates the number of prescriptions written in the United States, and thus the estimates provided in this paper are a lower bound of the potential effect.

Lastly, using data from the National Plan and Provider Enumeration System, I have added additional data on the attending physician associated with each visit, namely his or her specialty (i.e., health care provider taxonomy codes), gender, and whether he or she is a sole proprietor. [36] The billing data are reported by NJDHSS at the patient visit level. Each diagnosis is classified by an International Classification of Diseases (ICD) code, as published by the U.S. Public Health Service. These codes can be up to six digits long; I aggregate these to the 2-digit level. [37] Because I am primarily concerned with the behavior of physicians, I have aggregated these data to the level of the doctor-hospital-diagnosis for each month. This allows us to examine how the behavior of a given doctor changes within a diagnosis, thus eliminating any concerns over variation within the patients' disease profile. I begin with 12 million patient visits for 18 thousand physicians from 2009-2010. In order to narrow the

[36] Administered by the Centers for Medicare and Medicaid, https://nppes.cms.hhs.gov/

[37] ICD-9 codes are similar to industry classification codes in that additional digits provide additional detail about the disease. For instance, diseases of the respiratory system are ICD codes 460 to 519; codes beginning with 46 (460-466) are acute respiratory infections; 466 is acute bronchitis and bronchiolitis; 466.11 is acute bronchiolitis due to RSV, etc. While the full ICD-9 code is significantly more granular than the two digit level, and therefore would increase the total number of observations, it would also result in a highly imbalanced panel

sample to potential prescribers, i.e., physicians in specialties and/or treating diagnoses with the potential to have drugs prescribed, I will restrict the sample to prescribers only. I define prescribers as physicians who have written at least one prescription in the hospital between 2008 and 2010. Thus while the sample will still include physicians who did not prescribe at all in the period of interest between 2009 and 2010, these doctors were at least *potential* prescribers. Table 1 provides details on various physician characteristics, including payment status, for both potential prescribers and nonprescribers.

After collapsing these down to the physician-hospital-diagnosis-month level and discarding physicians who never write a single prescription in the data, I am left with 428,499 observations. Among these, 8,612 come from physicians who received at least one payment from GSK. Table 1 provides descriptive statistics for the physicians in this dataset.

IV. Estimation Strategy

In order to estimate the effect of withdrawing payments on a physician's prescription behavior, I will employ a differences-in-differences model. I specify an OLS regression that includes fixed effects for both physician and diagnosis. In this case, the key variables of interest will be the status of the physician's payment (i.e., whether the payment was withdrawn or not) interacted with the year of observation. In this case, because no payments are observed before 2009, I will be comparing physicians who had their payments cut in 2009 (when they received the payment) and 2010 (when the payment had been withdrawn). Thus the interaction between payment status and year will indicate the effect of withdrawing a payment for a given physician treating a particular diagnosis.

To fully address the impact of withdrawing payments, I will examine a number of dimensions of prescribing behavior as the dependent variable for this estimation: the share of a doctor's patients in a given month who were prescribed drugs; the share of a doctor's patients who were prescribed branded drugs; the total number of prescriptions written; the number of branded prescriptions written; and the ratio of branded prescriptions out of total prescriptions written. Table 2 describes each of these variables for 2009 and 2010.

The specification for physician *i* treating diagnosis *j* at hospital *h* in period *t* is:

$$
\begin{aligned}
& Share\ of\ branded\ drugs_{ijht} \\
& \qquad = \beta_0 + \beta_1 Payment\ Status_i + \beta_2 Year_t + \beta_3 Payment\ Status_i * Year_t \\
& \qquad + Patient\ Profile_{ijht} + Diagnosis_j + Physician/Hospital_{ih} + \varepsilon_{ijht}
\end{aligned}
$$

The dependent variable will naturally vary as we examine different dimensions of prescribing behavior; however, the specification will remain the same. The year term will address any overall time-trends such as patent expirations. For the physician's patient profile, I include the patient characteristics that have been demonstrated to have a significant impact on prescribing decisions: average patient age, share of patients with an HMO as their primary payer, and share of patients who were inpatients.[38] The inclusion of diagnosis and physician fixed effects are crucial, and will be included in every estimation. The diagnosis fixed effect is critical to control for the availability of drugs, whether branded or generic, that are relevant for treatment. As before, I include a fixed effect for each physician-hospital pair (i.e., a physician at a given hospital, rather than separate fixed effects for both the physician and the hospital) in order to control for any idiosyncratic financial arrangements between the physician and the hospital that might affect prescribing behavior, while also controlling for a physician's time- and diagnosis-invariant prescribing habits.

[38] A measure of patient acuity.

V. RESULTS

Figure 2 summarizes the key independent variables in each table, and in each specification the variables of interest are in bold. In every specification, the omitted category is physicians who did not receive payments in 2009 or 2010 that were disclosed. Model 1 includes fixed effects for diagnosis and physician-hospital pairs, and Model 2 adds patient controls. For specifications with dependent variables that are simple counts (total generic drugs prescribed and total branded drugs prescribed), only Models 1 and 2 are included. For the remaining specifications where the dependent variable is a percentage, Model 3 includes analytic weights to account for the actual number of patients that a physician sees in a given month.

Table 3 presents the effect on prescribing for physicians whose payments from GSK were reduced between 2009 and 2010. The 2010 coefficient is negative and significant for generic drugs prescribed, branded drugs prescribed, and the share of patients prescribed drugs overall or branded drugs specifically. Clearly, the overall trend in treatment was to use fewer drugs of any type. The remainder of the discussion will focus on changes relative to this overall trend.

In Table 3, the only independent variable of interest that attains significance is the trend in generic drugs prescribed. Physicians who had their payments reduced by GSK increased the number of generic drugs they prescribed relative to other doctors, but not the share of patients receiving these drugs. This implies that generic prescriptions per patient increased, behavior which suggests support for physician learning. Table 4 further subdivides this effect into physicians who had their payments from GSK reduced but not cut off entirely, and those whose GSK payments were completely stopped. These results illustrate that the effect shown in Table 3 of reducing payments is driven by physicians who had their payments cut entirely, not simply reduced. Physicians who received reduced payments did not alter their behavior significantly differently than any other physician. Taken together, these results suggest that Proposition 1 is incorrect—reducing payments to physicians without cutting them does not significantly change their prescribing behavior—while Proposition 2 is supported.

Finally, Table 5 examines physicians who had their payments from GSK cut entirely, and subdivides this group into physicians who were still receiving payments from other companies in 2010, and those who were not (the "Cut off" group). Excluding physicians who were cut off entirely alters the magnitude of the coefficient for generic prescriptions slightly; for all physicians with payments from GSK cut, generic prescriptions increased by 0.188, whereas if you exclude physicians who were receiving no other payments, it falls to 0.177 (both significant above the 99% level). Physicians whose payments were cut off by GSK and had no other payments were quite different, however. Like their peers who were still receiving payments, they significantly increased the number of generic prescriptions written. But they also significantly increased their branded prescriptions, as well as the shares of patients for whom they were writing prescriptions, branded and overall (all significant above the 99% level). This supports Proposition 3—physicians who did not have payments from other companies had much more diffuse prescribing behavior than those who did.

VI. Conclusions and Future Directions

In spite of arguments to the contrary, the results presented in this paper strongly support the conclusion that outside financial arrangements have a significant persuasive impact on decision-making. While the informational value of pharmaceutical industry payments to physicians has been demonstrated elsewhere, the results of this paper confirm the existence of a purely persuasive effect from these payments as well. It will not come as surprise to many people that having an external financial incentive will alter behavior. However, this paper has also demonstrated that conflicts of interest are not completely analogous to other types of incentives; I demonstrate that, contrary to the reciprocity-type behavior that has been found in response to reducing payments in more traditional incentive schemes, doctors who had their payments reduced (but not cut) did not significantly alter their behavior relative to physicians who had never received a payment at all.

The results of the analysis presented in this paper further suggest that when payments are removed, physicians learn about unfamiliar substitutes by experimenting and prescribing a larger number of drugs, both branded and generic. Absent data on specific brands, it is impossible to tell the exact nature of this experimentation; do these physicians pursue something like a trigger strategy and "punish" the company for withdrawing their payments by substituting to competitors? We saw that physicians who were cut off entirely and had no payments from other companies prescribed even more drugs than those who still had loyalties to other companies—are these prescriptions concentrated on a few substitutes or many? The answers to such questions will be a fruitful avenue for future research, both within the pharmaceutical industry as well as for other industries where conflicts of interest may undermine a firm's objectives.

The most important dimension of this debate that this paper cannot address is patient outcomes. My results suggest that receiving payments from a pharmaceutical company may restrict physicians prescribing choices—prior to having their payments cut off, were physicians who received payments more concentrated in their prescribing choices than the average physician? And if so, what are the implications of such concentration for performance—did physicians who did not receive payments or who had their payments cut off achieve better patient outcomes? While this paper has demonstrated the existence of a persuasive effect of an external financial relationship, this does not refute the existence of real informational benefits as well. Ultimately, it is the balance of these two effects that will determine appropriate solutions for this question, and measuring actual performance will be crucial for research in this area going forward.

FIGURES

Figure 1: Effect of a New Payment from GSK

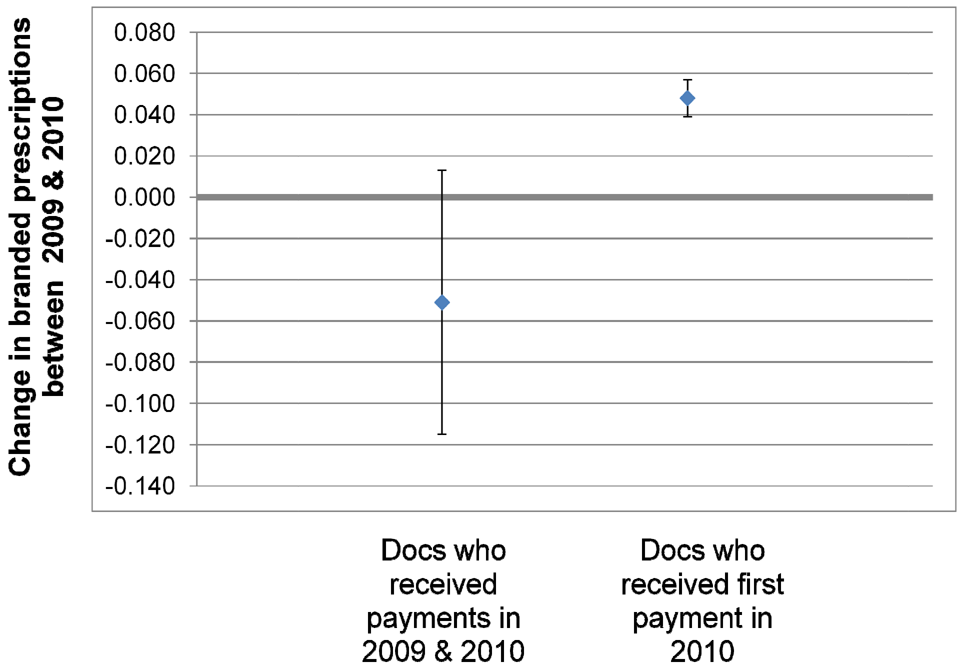
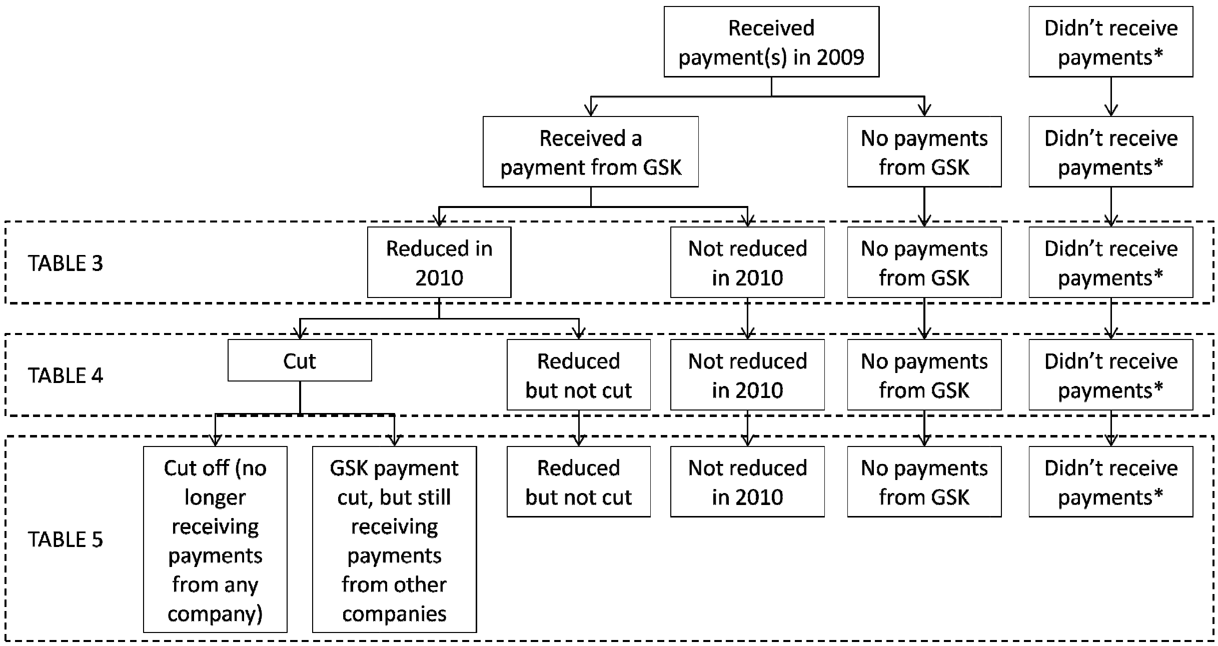


Figure 2: Summary of Physician Payment Statuses



TABLES

Table 1: Descriptive Statistics on Physicians

All Prescribers*

	Average	St. Dev.	Minimum	Maximum
Payment Received	$ 569.82	$ 4,730.51	$ -	$ 278,878.60
Companies receiving payments from	0.269	0.594	0	6
Sole Proprietor	0.272	0.445	0	1
Female	0.251	0.433	0	1
Observations	428,499			

Prescribers who received payments from GSK

	Average	St. Dev.	Minimum	Maximum
Payment Received from All Companies	$ 15,591.66	$ 25,033.94	0	$ 278,878.60
Companies receiving payments from	1.599	1.140	0	6
Sole Proprietor	0.273	0.446	0	1
Female	0.034	0.182	0	1
Observations	8,612			

Non-prescribers

	Average	St. Dev.	Minimum	Maximum
Payment Received	$ 406.44	$ 4,756.84	0	$ 428,102.00
Companies receiving payments from	0.189	0.500	0	7
Sole Proprietor	0.259	0.438	0	1
Female	0.287	0.452	0	1
Observations	898,796			

* Physicians who wrote at least one prescription in any hospital for any diagnosis between 2008 - 2010.

Table 2: Descriptive Statistics on Dependent Variables

All Prescribers*

	Average	St. Dev.	Minimum	Maximum
Total Generic Drugs Prescribed	0.443	1.959	0	136
Total Branded Drugs Prescribed	0.086	0.660	0	111
Branded scrips as a share of total prescriptions	0.150	0.295	0	1
Share of Patients Prescribed Drugs	0.196	0.381	0	1
Share of Patients Prescribed Branded Drugs	0.048	0.209	0	1
Patients seen per month**	2.295	4.928	1	318

Prescribers who received payments from GSK

	Average	St. Dev.	Minimum	Maximum
Total Generic Drugs Prescribed	0.38992	0.9427	0	18
Total Branded Drugs Prescribed	0.13237	0.52519	0	14
Branded scrips as a share of total prescriptions	0.2055	0.30013	0	1
Share of Patients Prescribed Drugs	0.24349	0.42392	0	1
Share of Patients Prescribed Branded Drugs	0.08815	0.2797	0	1
Patients seen per month**	1.65362	1.54737	1	35

* Physicians who wrote at least one prescription in any hospital for any diagnosis between 2008 - 2010.

** Used for analytic weights

Table 3: Effect of Payment Reduction on Prescribing

	Branded scrips as a share of total prescriptions			Total Generic Drugs Prescribed		Total Branded Drugs Prescribed		Share of Patients Prescribed Drugs			Share of Patients Prescribed Branded Drugs		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GSK Payment Status	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
Year 2010	-0.001 (0.001)	-0.002 (0.001)	0.000 (0.001)	-0.251*** (0.028)	-0.251*** (0.028)	-0.033*** (0.004)	-0.033*** (0.004)	-0.027*** (0.002)	-0.026*** (0.002)	-0.018*** (0.002)	-0.003*** (0.001)	-0.003*** (0.001)	-0.002*** (0.000)
GSK payment reduced * 2010	**0.003 (0.008)**	**0.004 (0.007)**	**0.006 (0.008)**	**0.137** (0.057)**	**0.137** (0.057)**	**-0.022 (0.031)**	**-0.021 (0.031)**	**-0.01 (0.019)**	**-0.009 (0.019)**	**-0.009 (0.017)**	**0.004 (0.003)**	**0.004 (0.003)**	**0.007 (0.005)**
GSK payment not reduced * 2010	**0.010* (0.006)**	**0.009* (0.006)**	**0.009 (0.008)**	**0.004 (0.103)**	**0.004 (0.104)**	**-0.011 (0.033)**	**-0.011 (0.033)**	**-0.001 (0.014)**	**0.000 (0.014)**	**-0.004 (0.014)**	**0.002 (0.007)**	**0.002 (0.007)**	**0.003 (0.008)**
No payments from GSK * 2010	-0.003 (0.002)	-0.003* (0.002)	-0.004** (0.002)	0.038 (0.038)	0.038 (0.038)	-0.027* (0.016)	-0.027* (0.016)	-0.013*** (0.003)	-0.012*** (0.003)	-0.013*** (0.004)	-0.003** (0.001)	-0.002** (0.001)	-0.002** (0.001)
Didn't receive payments * 2010	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Doctor-Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ICD-9 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient Controls[1]	No	Yes	Yes	No	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes
Patient Weighting[2]	No	No	Yes	No	No	No	No	No	No	Yes	No	No	Yes
Constant	0.154*** (0.004)	0.111*** (0.007)	0.086*** (0.006)	0.485*** (0.012)	0.485*** (0.018)	0.087*** (0.004)	0.052*** (0.007)	0.236*** (0.004)	0.174*** (0.005)	0.183*** (0.005)	0.053*** (0.002)	0.017*** (0.003)	0.014*** (0.002)
R^2	0.874	0.876	0.916	0.27	0.27	0.384	0.384	0.73	0.732	0.784	0.758	0.761	0.811
N		99,495		428,499		428,499			428,499			428,499	

* p<.1, ** p<.05, *** p<.01

[1] Average patient age, HMO as primary payer, inpatient status

[2] Analytical weights of patient volume used for dependent variables that are averages

All standard errors are robust and clustered at the physician-hospital level

Table 4: Effect of Payment Cut on Prescribing

	Branded scrips as a share of total prescriptions			Total Generic Drugs Prescribed		Total Branded Drugs Prescribed		Share of Patients Prescribed Drugs			Share of Patients Prescribed Branded Drugs		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GSK Payment Status	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
Year 2010	-0.001	-0.002	0.000	-0.251***	-0.251***	-0.033***	-0.033***	-0.027***	-0.026***	-0.018***	-0.003***	-0.003***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.028)	(0.028)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	0.000
GSK cut * 2010	**0.004**	**0.008**	**0.005**	**0.188*** **	**0.188*** **	**-0.017**	**-0.016**	**0.013**	**0.013**	**0.01**	**0.004**	**0.004**	**0.005**
	(0.013)	**(0.012)**	**(0.010)**	**(0.049)**	**(0.049)**	**(0.034)**	**(0.034)**	**(0.010)**	**(0.010)**	**(0.010)**	**(0.003)**	**(0.003)**	**(0.003)**
GSK payment reduced (not cut) * 2010	**0.002**	**0.002**	**0.006**	**0.074**	**0.075**	**-0.028**	**-0.027**	**-0.038**	**-0.037**	**-0.032**	**0.004**	**0.004**	**0.01**
	(0.009)	**(0.010)**	**(0.011)**	**(0.095)**	**(0.095)**	**(0.053)**	**(0.053)**	**(0.039)**	**(0.038)**	**(0.035)**	**(0.006)**	**(0.005)**	**(0.011)**
GSK payment not reduced * 2010	0.010*	0.009*	0.009	0.004	0.004	-0.011	-0.011	-0.001	0.000	-0.004	0.002	0.002	0.003
	(0.006)	(0.006)	(0.008)	(0.103)	(0.104)	(0.033)	(0.033)	(0.014)	(0.014)	(0.014)	(0.007)	(0.007)	(0.008)
No payments from GSK * 2010	-0.003	-0.003*	-0.004**	0.038	0.038	-0.027*	-0.027*	-0.013***	-0.012***	-0.013***	-0.003**	-0.002**	-0.002**
	(0.002)	(0.002)	(0.002)	(0.038)	(0.038)	(0.016)	(0.016)	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Didn't receive payments * 2010	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Doctor-Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ICD-9 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient Controls[1]	No	Yes	Yes	No	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes
Patient Weighting[2]	No	No	Yes	No	No	No	No	No	No	Yes	No	No	Yes
Constant	0.154***	0.111***	0.086***	0.486***	0.486***	0.087***	0.052***	0.236***	0.174***	0.183***	0.053***	0.017***	0.014***
	(0.004)	(0.007)	(0.006)	(0.012)	(0.018)	(0.004)	(0.007)	(0.004)	(0.005)	(0.005)	(0.002)	(0.003)	(0.002)
R^2	0.874	0.876	0.916	0.27	0.27	0.384	0.384	0.73	0.732	0.784	0.758	0.761	0.811
N	99,495			428,499		428,499		428,499			428,499		

* p<.1, ** p<.05, *** p<.01

[1] Average patient age, HMO as primary payer, inpatient status

[2] Analytical weights of patient volume used for dependent variables that are averages

All standard errors are robust and clustered at the physician-hospital level

Table 5: Effect of Payment Cut on Prescribing When No Other Payments Received

	Branded scrips as a share of total prescriptions			Total Generic Drugs Prescribed		Total Branded Drugs Prescribed		Share of Patients Prescribed Drugs			Share of Patients Prescribed Branded Drugs		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GSK Payment Status	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
Year 2010	-0.001	-0.002	0.000	-0.251***	-0.251***	-0.033***	-0.033***	-0.027***	-0.026***	-0.018***	-0.003***	-0.003***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.028)	(0.028)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	0.000
Cut off * 2010	**0.012**	**0.011***	**0.012***	**0.261*****	**0.258*****	**0.034*****	**0.033*****	**0.024*****	**0.023*****	**0.017*****	**0.003*****	**0.003*****	**0.002*****
	(0.008)	**(0.006)**	**(0.006)**	**(0.034)**	**(0.034)**	**(0.005)**	**(0.005)**	**(0.005)**	**(0.005)**	**(0.003)**	**(0.001)**	**(0.001)**	**(0.001)**
GSK cut, but still receiving payments from others *	**0.004**	**0.008**	**0.005**	**0.177*****	**0.178*****	**-0.024**	**-0.024**	**0.011**	**0.012**	**0.009**	**0.004**	**0.005**	**0.005**
	(0.013)	**(0.012)**	**(0.010)**	**(0.052)**	**(0.052)**	**(0.038)**	**(0.038)**	**(0.012)**	**(0.012)**	**(0.011)**	**(0.004)**	**(0.004)**	**(0.004)**
GSK payment reduced (not cut) * 2010	0.002	0.002	0.006	0.074	0.075	-0.028	-0.027	-0.038	-0.037	-0.032	0.004	0.004	0.01
	(0.009)	(0.010)	(0.011)	(0.095)	(0.095)	(0.053)	(0.053)	(0.039)	(0.038)	(0.035)	(0.006)	(0.005)	(0.011)
GSK payment not reduced * 2010	0.010*	0.009*	0.009	0.004	0.004	-0.011	-0.011	-0.001	0.000	-0.004	0.002	0.002	0.003
	(0.006)	(0.006)	(0.008)	(0.103)	(0.104)	(0.033)	(0.033)	(0.014)	(0.014)	(0.014)	(0.007)	(0.007)	(0.008)
No payments from GSK * 2010	-0.003	-0.003*	-0.004**	0.038	0.038	-0.027*	-0.027*	-0.013***	-0.012***	-0.013***	-0.003**	-0.002**	-0.002**
	(0.002)	(0.002)	(0.002)	(0.038)	(0.038)	(0.016)	(0.016)	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Didn't receive payments * 2010	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Doctor-Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ICD-9 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient Controls[1]	No	Yes	Yes	No	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes
Patient Weighting[2]	No	No	Yes	No	No	No	No	No	No	Yes	No	No	Yes
Constant	0.154***	0.111***	0.086***	0.485***	0.485***	0.087***	0.052***	0.236***	0.174***	0.183***	0.053***	0.017***	0.014***
	(0.004)	(0.007)	(0.006)	(0.012)	(0.018)	(0.004)	(0.007)	(0.004)	(0.005)	(0.005)	(0.002)	(0.003)	(0.002)
R^2	0.874	0.876	0.916	0.27	0.27	0.384	0.384	0.73	0.732	0.784	0.758	0.761	0.811
N		99,495		428,499		428,499			428,499			428,499	

* p<.1, ** p<.05, *** p<.01

[1] Average patient age, HMO as primary payer, inpatient status

[2] Analytical weights of patient volume used for dependent variables that are averages

All standard errors are robust and clustered at the physician-hospital level

REFERENCES

Berndt, Ernst R., Margaret Kyle, and Davina Ling. 2003. "The Long Shadow of Patent Expiration. Generic Entry and Rx-to-OTC Switches". NBER Chapters. National Bureau of Economic Research, Inc. http://ideas.repec.org/h/nbr/nberch/9737.html.

Carter, Craig R. 2000. "Precursors of Unethical Behavior in Global Supplier Management." *Journal of Supply Chain Management* 36 (1): 45–56. doi:10.1111/j.1745-493X.2000.tb00069.x.

Chatterji, Aaron K., Kira R. Fabrizio, Will Mitchell, and Kevin A. Schulman. 2008. "Physician-Industry Cooperation In The Medical Device Industry." *Health Affairs* 27 (6) (November 1): 1532–1543. doi:10.1377/hlthaff.27.6.1532.

Cooper, Robert W., Garry L. Frank, and Robert A. Kemp. 1997. "The Ethical Environment Facing the Profession of Purchasing and Materials Management." *International Journal of Purchasing and Materials Management* 33 (1): 2–11. doi:10.1111/j.1745-493X.1997.tb00286.x.

Geletkanycz, Marta A., and Donald C. Hambrick. 1997. "The External Ties of Top Executives: Implications for Strategic Choice and Performance." *Administrative Science Quarterly* 42 (4) (December 1): 654–681. doi:10.2307/2393653.

Gino, Francesca, and Max H. Bazerman. 2009. "When Misconduct Goes Unnoticed: The Acceptability of Gradual Erosion in Others' Unethical Behavior." *Journal of Experimental Social Psychology* 45 (4) (July): 708–719. doi:10.1016/j.jesp.2009.03.013.

Handfield, Robert B., and David L. Baumer. 2006. "Managing Conflict of Interest Issues in Purchasing." *Journal of Supply Chain Management* 42 (3): 41–50. doi:10.1111/j.1745-493X.2006.00016.x.

Hanssens, Dominique. 2011. "What Is Known About the Long-Term Impact of Advertising". Marketing Accountability Standards Board.

Haunschild, Pamela R. 1993. "Interorganizational Imitation: The Impact of Interlocks on Corporate Acquisition Activity." *Administrative Science Quarterly* 38 (4) (December 1): 564–592. doi:10.2307/2393337.

Kube, Sebastian, Michel Maréchal, and Clemens Puppe. 2010. "Do Wage Cuts Damage Work Morale? Evidence from a Natural Field Experiment". SSRN Scholarly Paper ID 1547823. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1547823.

Larkin, Ian, Lamar Pierce, and Francesca Gino. 2012. "The Psychological Costs of Pay-for-performance: Implications for the Strategic Compensation of Employees." *Strategic Management Journal* 33 (10): 1194–1214. doi:10.1002/smj.1974.

Leffler, Keith B. 1981. "Persuasion or Information - The Economics of Prescription Drug Advertising." *Journal of Law & Economics* 24: 45.

Lipton, Eric, and Kevin Sack. 2013. "Medicare Pricing Delay Is Political Win for Amgen, Drug Maker." *The New York Times*, January 19, sec. U.S. http://www.nytimes.com/2013/01/20/us/medicare-pricing-delay-is-political-win-for-amgen-drug-maker.html.

Meier, Barry. 2012. "Opioid Painkiller Prescriptions Pose Danger Without Oversight." *The New York Times*, April 8, sec. Health. http://www.nytimes.com/2012/04/09/health/opioid-painkiller-prescriptions-pose-danger-without-oversight.html.

Moore, Don A. 2005. *Conflicts of Interest: Challenges and Solutions in Business, Law, Medicine, and Public Policy*. Cambridge University Press.

Moore, Don A., Philip E. Tetlock, Lloyd Tanlu, and Max H. Bazerman. 2006. "Conflicts Of Interest And The Case Of Auditor Independence: Moral Seduction And Strategic Issue Cycling." *Academy of Management Review* 31 (1) (January 1): 10–29. doi:10.5465/AMR.2006.19379621.

Ramanarayanan, Subramaniam. 2008. "Does Practice Make Perfect: An Empirical Analysis of Learning-by-Doing in Cardiac Surgery". SSRN Scholarly Paper ID 1129350. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1129350.

Rosenstein, Stuart, and Jeffrey G. Wyatt. 1994. "Shareholder Wealth Effects When an Officer of One Corporation Joins the Board of Directors of Another." *Managerial and Decision Economics* 15 (4): 317–327. doi:10.1002/mde.4090150406.

Semin, Dilek Güldal and Semih. 2000. "The Influences of Drug Companies Advertising Programs on Physicians." *International Journal of Health Services* 30 (3) (July 1): 585–595. doi:10.2190/GYW9-XUMQ-M3K2-T31C.

Smith, M. A., E. D. Cox, and J. M. Bartell. 2006. "Overprescribing of Lipid Lowering Agents." *Quality and Safety in Health Care* 15 (4) (August 1): 251–257. doi:10.1136/qshc.2005.016162.

Taub, Anna A. Levine, Anton Kolotilin, Robert S. Gibbons, and Ernst R. Berndt. 2011. "The Diversity of Concentrated Prescribing Behavior: An Application to Antipsychotics". Working Paper 16823. National Bureau of Economic Research. http://www.nber.org/papers/w16823.

Yermack, David. 2004. "Remuneration, Retention, and Reputation Incentives for Outside Directors." *The Journal of Finance* 59 (5): 2281–2308. doi:10.1111/j.1540-6261.2004.00699.x.