First, Do No Harm: Financial Conflicts in Medicine*

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Abstract: We explore financial conflicts of interest faced by doctors. Pharmaceutical firms frequently pay physicians in the form of meals, travel, and speaking fees. Over half of the 334,000 physicians in our sample receive payment of some kind. When a doctor is paid, we find that he is more likely to prescribe a drug of the paying firm, both relative to close substitutes and even generic versions of the same drug. This payment-for-prescription effect scales with transfer size, although doctors receiving only small and/or infrequent payments are also affected. The pattern holds in nearly every U.S. state, but it is strongly and positively related to regional measures of corruption.

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I. Introduction

When an informed buyer enlists the help of an expert, the potential for conflicts of interest often arises. Take for example a wine sommelier working at a fine restaurant. Is the recommended Pinot Noir the optimal choice for a given meal, or has the restaurant encouraged the sommelier to push a particular brand, perhaps trying to rid itself of a few extra bottles?

While such rent-seeking behavior might not surprise many people – who hasn't questioned the necessity of an auto repair – that financial conflicts of interest could influence their doctor's advice might be both less expected and more worrisome. For one, doctors are already highly paid, with most falling in the top 5% of the U.S. income distribution within the US (BLS 2010; Census 2010). Moreover, intrinsic motivation is thought to be important in medicine, with the goal of optimizing patient health being a paramount objective (Heyes 2005; Rebitzer and Taylor 2011).

On the other hand, this need not coincide with the objective of pharmaceutical firms, who have strong incentives to maximize prescriptions. Thus, when drug companies have financial relationships with physicians, the potential for biased decision-making arises.

This possibility has not gone unnoticed by legislators. Beginning in 2014, the Physician Payments Sunshine Act will take effect, when drug and medical device manufacturers will be required to publicly report payments to physicians and teaching hospitals (CMS 2013). And, although difficult to argue with higher levels of transparency in almost any setting, the more important question here is whether conflicts of interest influence physician behavior. That is, do doctors with connections to the pharmaceutical industry behave differently than those lacking such financial relationships?

To explore this issue, we collect data on payments to physicians provided on the *Dollars for Docs* website, hosted by independent journalist consortium ProPublica (ProPublica 2013a).

Dollars for Docs is a searchable web interface allowing a user to observe transfers from pharmaceutical firms to specific physicians since 2009. As of 2011, twelve companies reported payments, including most of the major firms, e.g., Pfizer, Merck, GlaxoSmithKline, AstraZeneca, and Johnson & Johnson. Although reporting is not standardized (yet, see above), most firms break down payments by dollar amount and type, such as gifts, meals, speaking, travel, consulting, and on occasion, proprietary research.

To this dataset we merge prescription information for each doctor as reported from Medicare (Part D) reimbursements, also provided by ProPublica on its *Prescriber Checkup* website (ProPublica 2013b). This combination allows us to conduct cross-sectional regressions comparing prescribing patterns of doctors who differ in whether, or how much, they are paid by a given drug company.

As a motivating anecdote, consider the prescription choices of two suburban New Jersey internists, "A.P." and "G.G." High cholesterol is one of the most commonly treated conditions in the U.S., and accordingly, two of the top eight selling name-brand prescription drugs in 2010 were "statins" Lipitor, marketed by Pfizer, and Crestor, marketed by AstraZeneca. Though widely viewed as close substitutes, Lipitor appeared to be strongly preferred by physician A.P. (579 prescriptions versus 52 for Crestor), with G.G. favoring Crestor (1,584 versus 1,010). While generally, one might expect differences in patient demographics or disease incidence may cause doctors to prefer one drug over another, that claim is harder to make in this particular case, with numerous studies showing very similar efficacy between the two drugs (Nicholls et al. 2011; Luvai et al. 2012). Of perhaps more relevance is that in 2010, A.P. received payments in excess of $12,000 from Pfizer for meals, travel, and speaking fees (versus $182 from AstraZeneca), whereas G.G. was compensated over $2000 by AstraZeneca and nil by Pfizer.

Such comparisons generalize to our sample of some 334,000 doctors, which includes roughly half of all physicians licensed in the U.S. Pairing each doctor i in our sample to each of

the twelve pharmaceutical firms *j*, we ask whether *j* to *i* transfers are associated with more prescriptions for company *j*'s drugs written by doctor *i*. Unconditionally, the typical doctor in our sample has about a 13% chance of actively prescribing a given pharmaceutical firm's drugs, defined as prescribing 50 or more of any of its products. But, this jumps to almost 30% if we observe that the pharmaceutical firm pays the doctor for meals, speaking fees, consulting, or other activities. Alternatively, if a pharmaceutical firm doubles the amount a doctor receives (about $1700 on average for paid physicians), we observe an increase in the neighborhood of 7-9 additional prescriptions.

With these basic findings established, the remainder of the paper attempts to better understand the mechanism, and in so doing, infer whether close relationships between doctors and drug companies likely lead to better or worse outcomes for patients. We explore three hypotheses: doctors can be 1) transmitters of information, 2) consumers of information, or 3) rent seekers.

In the first alternative, pharmaceutical firms are simply paying for a doctor's expertise or information. As a simple example, consider a pharmaceutical representative sharing a meal with a doctor who already prescribes the firm's drugs frequently, and thus, is a valuable source of information regarding side effects, patient compliance, etc. In this case, provided that prescription decisions are not made in anticipation of future monetary benefits – which is just rent seeking with different timing – payments from drug companies play no role in a doctor's behavior, and indeed, may ultimately help pharmaceutical companies design better drugs.

Paying physicians for information appears to represent only a small minority of the transfers we observe. For one, compensation for consulting and research – activities most likely to reflect a physician's expertise – occurs rarely, comprising less than 3% of the transfers we observe. Further, the payment-prescription relation holds strongly even excluding the most heavily prescribed drugs by each physician. Here, the payment-prescription effect is identified

from variation in drugs unlikely to represent an area of expertise, such as ophthalmologists prescribing cholesterol reducers, gynecologists prescribing anti-seizure medications, and so on.

Another possible mechanism is that doctors may be receivers, rather than transmitters of information. For example, pharmaceutical firms engage in "detailing," marketing which attempts to inform (or perhaps persuade) doctors to use pharmaceutical products (Dave 2013). To mitigate this possibility, we conduct a number of head-to-head comparisons between drugs that are not only similar or identical chemically, but also have been on the market for several years. Both factors, ostensibly, should reduce a physician's information deficit.

The first of such comparisons is between cholesterol reducing statins Lipitor and Crestor, the pair of cholesterol-reducing drugs mentioned in the prior anecdote. Statins are the most widely prescribed class of drugs in the U.S., amounting for more than 255 million prescriptions in 2010.[1] Moreover, this class of drugs has several generic and brand options on the market, all of which had been available for several years. Yet, we nevertheless find that Pfizer payments tilt the balance in favor of Lipitor (with larger payments having a bigger effect), with AstraZeneca payments being associated with more prescriptions of Crestor. Moreover, we find that payments from *either* company reduce the fraction of generic statin alternatives prescribed.

Similar patterns are observed between a number of branded drugs and their generic equivalents – i.e., not simply drugs in the same drug class. That we find a positive payment-prescription relation here is hard to square with information flow from drug companies, even for the most uninformed or naïve doctors.

Last, it is possible that prescription decisions are influenced by rent seeking and/or corruption, whereby a physician's relationships with drug companies represent opportunities for

[1] http://pharma.about.com/od/Sales_and_Marketing/a/The-Most-Prescribed-Medications-By-Drug-Class.htm

private benefits. Here, payments themselves have a causal impact on prescriptions, beyond the types of marketing or information effects described above. Moreover and importantly, the implications are, at least weakly, worse for patients.

As we did for the other alternatives, we examine subsets of the data where the effects of corruption, if true, should be strongest. Our first test uses data on federal convictions of corruption-related crime (Glaeser and Saks 2006) to proxy for the corruption rate of each U.S. state. Comparing the least corrupt U.S. states (e.g., Minnesota, Oregon, Nebraska) to the most corrupt (e.g., Louisiana, Mississippi, Illinois), we find that the prescription-payment magnitude is cut by nearly 50%. This is particularly striking given that the most corrupt states are among the poorest (many in the Southeast), and yet the ratio of branded-to-generic drugs is highest in precisely this region.

Our second test is between male and female doctors. Using an algorithm to classify doctor first names by gender, we find that men are over twice as sensitive to payments versus women. This confirms experimental and field evidence suggesting that women are more honest and less corruptible than men (e.g. Dollar, Fisman, and Gatti 2001).

Our findings also provide an empirical benchmark for assessing the impact of the upcoming Sunshine Act of 2014, given that our sample predates its implementation by four years and even most discussion by two years. Although only a portion of our analysis can distinguish between persuasive advertising and rent-seeking behavior, these mechanisms need not be separated in order for the Sunshine Act to be warranted. Specifically, if either welfare-reducing phenomenon exists then its effects may be ameliorated by the legislated transparency of pharmaceutical firm payments.

The idea that physicians face potential conflicts of interest is not new (American College of Physicians 1990; Medicare Payment Advisory Committee 2009). For example, well after ethical standards describing appropriate relationships between pharmaceutical firms and

physicians were developed, there was substantial concern that payments affect or reward clinical behavior (Coyle 2002). Controversy remains in part because existing empirical evidence characterizing pharmaceutical industry and physician relationships relies almost exclusively on opinion surveys (Madhavan et al. 1997; Wazana 2000; Katz, Caplan, and Merz 2010), rather than on directly observed clinical behavior.

Notable exceptions include Larkin et al. (2012), which identifies a causal effect of detailing on prescriptions using changes in hospital policies in six metropolitan areas, and Pham-Kanter et al. (2012) which compares prescription behavior at the state level between states which disclose pharmaceutical payments and those which do not. The critical component of our study is the availability of both prescription and payment data for over 330,000 individual physicians in every U.S. state, a breadth which not only allows us to identify an effect of individual payments on individual prescriptions, but also helps us specify the mechanism which generates the effect.

The remainder of the paper is organized as follows. In Section II, we describe our payment and prescription data and provide summary statistics. Section III provides evidence of a positive relationship between payments and prescriptions, while Section IV explores potential mechanisms. We conclude in Section V.

II. Data

We draw on several data sources to study the relationship between industry payments and physician prescribing behavior. First, we construct a listing of payments from pharmaceutical firms to doctors using ProPublica's *Dollars for Docs* database(ProPublica 2013a). ProPublica is an investigative journalism newsroom that makes data available on industry payments and prescribing patterns. *Dollars for Docs* is an online, searchable database of payments made publicly available by pharmaceutical firms, either voluntarily or due to legal

settlements. Data involving payments from twelve pharmaceutical over the period 2009-2011 were downloaded. Each observation is from a named pharmaceutical firm to a named provider and includes time period (year), payment type, and specific or categorical dollar amount.

Table 1 lists several summary statistics of reported payments to providers separated by pharmaceutical firm in Panel A and meal category in Panel B. Reporting is voluntary or arising from legal settlements and is therefore idiosyncratic. Casual inspection of Table 1 suggests these idiosyncrasies explain much of the variation across pharmaceutical firms in the number of providers that receive payment. For example, Merck only reported payments made for speaking over the 2009 to 2011 period. Because payments for speaking are less common, we identify approximately 2,000 providers to whom Merck made annual payments. On the other hand, AstraZeneca began reporting only speaking fees in 2010 but increased its scope for reporting to include meals, gifts, consulting, research and travel in 2011. This expanded disclosure by AstraZeneca increased the number of providers receiving payment from 2,381 in 2010 to 116,643 in 2011. Looking at the last row of Panel A, the total dollar amount of payments made by pharmaceutical firms increases substantially, from $188.86 million in 2009 to $773.05 million in 2011, driven primarily by expanded disclosure (as in the AstraZeneca example).

The average dollar amount and prevalence of payments also vary considerably by type of payment. For example, most reported research payments were greater than $10,000, but they were relatively infrequent. Reported consulting, speaking, and travel payments were also large, with many payments in those categories totaling in the thousands. In contrast, the median reported payments for gifts and meals were $72 and $37, respectively, and reported meal payments were by far the most frequent, comprising more than three-quarters of all reported payments.

ProPublica also provides a database of prescribing patterns called *Prescriber Checkup* (ProPublica 2013b). *Prescriber Checkup* is a searchable database of health care providers and

the number of Medicare Part D prescriptions (including refills) written for specific drugs in 2010 when that provider's number of such prescriptions exceeded 50 (to protect patient confidentiality). Importantly, these data comprise the universe of such provider-prescription information for the U.S. in 2010. ProPublica aggregated these data from 2010 Medicare Part D insurance claims that were obtained from the Centers for Medicare and Medicaid Services under a Freedom of Information Act request. The unit of observation in the *Prescriber Checkup* database is (Doctor, Drug), so for each doctor we observe how many Medicare Part D prescriptions were written for each drug. We use drug names to match drugs to their appropriate pharmaceutical firm (e.g., Lipitor matches with Pfizer). Of the 1,685 drugs in the *Prescriber Checkup* database, 239 match to one of our twelve pharmaceutical firms.[2]

The *Prescriber Checkup* database also includes summary information by doctor including the total number of Medicare Part D claims, the total number of patients receiving at least one claim, and identifying information such as name, city, state and medical specialty. We downloaded the *Prescriber Checkup* database and used the identifying information to match providers from the *Prescriber Checkup* database to the *Dollars for Docs* database. Table 2 provides some summary statistics from the matched sample. Of the 334,086 doctors in the *Prescriber Checkup* database we identify 192,484 (58%) as having received at least one payment from our twelve pharmaceutical firms between 2009 and 2011. Panel A of Table 2 also suggests that doctors who are paid by pharmaceutical firms are more active than those who are not. For example, the average doctor in our sample generated 2,980 Medicare Part D claims in 2010 from 217 patients (13.7 claims per patient). However, doctors who received payments from pharmaceutical firms generated 3,566 claims and saw 243 patients (14.7 claims per patient). Prescription rates are also higher for paid physicians among branded claims, i.e. prescriptions for drugs made by our twelve pharmaceutical firms. Panel A indicates that the average doctor

[2] The majority of drugs in the database are generics and, therefore, will not any pharmaceutical company which makes branded drugs.

generates 192 branded claims (0.88 per patient) but a paid doctor generates 258 branded claims (1.06 per patient).

Panel B of Table 2 provides summary statistics for (Doctor, Firm) pairs, which is the unit of observation in our main analysis. We choose (Doctor, Firm) rather than (Doctor, Drug) as the appropriate unit because we are unable to observe whether a payment was made to a doctor in connection with a specific drug; rather, we only observe total payments by each drug company to each doctor. Panel B indicates that when (Doctor, Firm) is the unit of observation we observe payments to doctors 11% of time among the over 4 million observations. When a payment is observed, the average size is $1,766 with a standard deviation of $21,403. Given the median payment is $57, the mean and standard deviation are strongly influenced by a handful of extremely large payments for research, speaking and consulting.

III. Pharmaceutical payments to physicians

We begin with the following question: in the cross-section of prescribing physicians, is receiving money from the pharmaceutical industry associated with different prescribing behavior?

To address this question, we consider payment and prescription behavior aggregated by state in Section A and progress towards finer units of observation, specifically doctors in Section B and (Doctor, Firm) pairs in Section C. Broad measures have the advantage of local idiosyncrasies washing out among a broad population. To the extent that we are concerned that a correlation between payments and prescriptions is generated by omitted local characteristics. On the other hand, micro-level analyses allow us to exploit more sources of variation (e.g., within doctor) when identifying a relationship between payments and prescriptions. We view both analyses as complementary and illustrative of the fact that a positive relationship exists between payments and prescriptions no matter how we slice the data.

A. States

Figure 1 depicts both the intensity of payment penetration into the population of providers (Panel A) and the intensity of branded prescriptions (Panel B). Specifically, we calculate by state the percentage of doctors receiving a payment from any pharmaceutical firm and plot the percentages via a heat map in Panel A. Recall from Table 2 that, unconditionally, 58% of doctors receive payments from pharmaceutical firms. However, there is significant geographic heterogeneity in payment rates, from Nevada with 68% to Minnesota with 16%, and an overall standard deviation across states of 13%.

Some of this heterogeneity can be explained by pharmaceutical firm location. For example, the state with the highest payment rate, New Jersey with 69%, is the corporate headquarters of both Merck and Johnson & Johnson. Indiana, home to Eli Lilly, has the seventh highest payment rate at 66% in marked contrast to its four neighbors, which have lower payment rates.

Panel B of Figure 2 shows a heat map of each state's "branded drug" prescription intensity, where branded drugs refer to the 239 marketed by any of the twelve drug companies in our set. (The remaining 1,685-239=1,446 are either generics or proprietary drugs by firms outside our twelve.) To calculate the fraction of branded claims we sum the number of Medicare prescriptions for these 239 drugs by state and scale by the total number of Medicare prescriptions by state. Again, we find plenty of heterogeneity across states with a mean of 6% and a standard deviation of 1.3%.

However, what is perhaps noteworthy about the heat map in Panel B is how similar it is to the heat map in Panel A. For example, New Jersey, the state with the highest payment rate, is also the state with the highest prescription rate of branded drugs (8.7%). Moreover, the disproportionate payment intensity which shows up in the Southeastern United States in Panel

A reappears as disproportionate branded prescription intensity in Panel B. Overall, the state-level correlation between the two series is 40% and is not sensitive to outliers. The rank (Spearman) correlation between the two series is 42%.

B. Doctors

The heat maps in Figure 1 provide broad evidence of a correlation between payment rates and prescriptions. In this section, we examine the relationship in greater detail by considering the distribution of prescription rates and payments *by doctor*. Recall that we observe for each doctor the specific number of prescriptions for each drug marketed by our twelve pharmaceutical firms, subject to at least fifty units being prescribed. We also observe for each doctor the total number of Medicare claims and patients. The opportunity to observe both types of prescriptions -- i.e., the brand name drugs manufactured by the twelve drug companies as well as non-brand name drugs – for each doctor turns out to be useful when making inferences about the effect of payments on prescribing behavior.

To see why, consider the following comparison. In our sample of 334,086 doctors, slightly fewer than half (154,654) did not receive payment from any pharmaceutical firm in our sample. For this group, the rate at which brand name drugs from any of our twelve firms was prescribed was 0.48 claims per patient. At the other end of the spectrum, the third- and second-to-highest decile of paid physicians (with payment amounts totaling several hundred dollars) prescribe brand name drugs at a much higher rate, respectively, at 0.80 and 0.96 claims per patient. Doctors in the top payment decile, with gifts, meals, speaking fees and other transfers exceeding thousands of dollars on average, prescribe brand name drugs at a rate of 1.20 per patient.

While these differences are large, causal inferences are made difficult by the fact that payments are endogenous to both doctor and patient characteristics. One obvious example is

that some specialties (e.g., internists) are more likely to prescribe drugs than others (e.g., orthopedic surgeons). Consequently, if drug companies disproportionately target specialties with high prescription rates, we would expect to find a correlation between payments and prescription rates, even if such targeting were completely ineffective. But, because we observe the rate at which each doctor prescribes drugs generally, i.e., outside of the brand names of interest, we can control for each doctor's baseline prescription intensity.

In Panel A of Figure 2, we show the results of the same sorting procedure described above, except that sorts are now conducted by decile of non-branded prescription rates. Specifically, we first place doctors into deciles ranked by average prescription rates using only non-branded (mostly generic) drugs. Each of these deciles is represented by a different shaded line in Figure 2, with the darkest line corresponding to the 10% most heavily prescribing doctors (about 30 non-branded claims per patient) and the lightest line to the 10% least prescribing doctors (about 2 non-branded claims per patient).

Then, within each of these deciles, we sort doctors based on the amount they receive from any of the pharmaceutical firms in our sample, from the least (none) on the far left, to the most on the far right. Starting with the darkest contour, we see an increase of about 50%, from roughly two brand-name claims per patient for doctors in the least-paid decile, to about three in the most. Moreover, most of the increase is in the last two deciles, which also corresponds to the steepest increase in payment amounts, both in percentages and dollars.

Moving down the figure we observe even larger increases in successive contours, with percentage differences between the unpaid and highest paid deciles of 129%, 150%, 184%, 184%, 213%, 175%, 79%, 49%, and 106%. Averaged across all groups, doctors in the top 20% of the payment distribution prescribe approximately twice the rate of brand name drugs compared to doctors in the bottom 20%.

The bottom panel (B) of Figure 2 shows the results of the same exercise, except that we are now plotting the prescription rates for non-brand name drugs. While initially this may seem uninformative given that contours in Panel A are formed by non-branded prescription rates, the concern is that sorting into ten groups may not be precise enough. If, for example, we found increasing non-branded prescription rates for each of our contours, we would be concerned that Panel A simply reflected further differences in prescription rates not captured by decile sorts.

However, Panel B shows that this is not the case. In virtually every decile, prescription rates for non-branded drugs decrease with payment, and most so between the 9th and 10th decile. Rather than prescription rates for brand-name drugs simply reflecting heterogeneity in baseline prescription frequencies, there is apparent substitution from non-brand name drugs to brand name drugs at a rate that increases with payments from the pharmaceutical industry.

Table 3 formalizes these univariate comparisons in linear regression coefficient estimates. We estimate:

$$\frac{Branded\ claims}{Total\ patients}_i = \alpha + \beta * Payments_i + \gamma * Controls_i + \varepsilon_i \qquad (1)$$

where *Branded claims* is all Medicare reimbursements for drugs prescribed by doctor *i* in year 2010, summed across all pharmaceutical firms *j* in our data set. Likewise, *Payments* is the sum of all payments received by doctor *i* by any pharmaceutical firm *j*, in any year from 2009-2011.[3] *Controls* include specialty fixed effects, state fixed effects, and the rate of non-branded prescriptions written by physician *i*.

In the first three columns, the sample is restricted to doctors with at least one payment from a pharmaceutical firm in our sample. With no doctor or location controls, the coefficient is a highly significant 0.087 (p<0.001). The interquartile range for the logarithm of total

[3] Because payments are so persistent within (Doctor, Pharma) pairs (see Table 4), the results are nearly identical if we instead restrict to payments occurring only in year 2010.

payments is 3.85-5.88=2.03, implying an increase in per-patient branded prescriptions of about 0.17, or roughly one-quarter of its mean value (0.66).

The second column adds controls for each of the 412 specialties listed by ProPublica and accounts for average differences in brand-name prescription rates across practice types. Although this adds considerable explanatory power to the regression, increasing the R^2 from 0.32 to 0.43, the coefficient on payments remains similar (0.0773, $p<0.001$). Likewise, state fixed effects give some account, though admittedly coarse, for differences in patient characteristics, which may be correlated with both brand-name prescription rates and pharmaceutical payments. However, the coefficient of interest remains significant, both economically and statistically.

The fourth, fifth, and sixth columns represent the closest analog to Figure 2. Here, we estimate equation (1) using indicator variables for each payment decile of payment, and a separate dummy variable for the group receiving no payments whatsoever. Decile construction is identical to the method described above. The omitted category is the fifth group, capturing the 40th to 50th percentiles of doctors ranked by payment.

Without exception in each specification, progressive payment deciles are associated with higher levels of branded prescriptions, and with roughly equivalent magnitude between specifications. With the middle quintile as the benchmark, doctors in the highest quintile write 40-50% more brand name prescriptions, while doctors in the lowest quintile write about 15% fewer. Thus, comparing the top and bottom quintiles gives close to the same 2-1 average ratio as that implied by the contours in Panel A of Figure 2.

C. Doctor-firm pairs

While the previous section suggests that paid doctors write more branded prescriptions, it does not exploit perhaps the most important variation in our data. Rather than ask whether a doctor who is paid by *any* of our twelve pharmaceutical firms is likely to prescribe *any* of their 239 drugs (as we did in the previous section), we can ask whether a doctor who is paid by a *specific* pharmaceutical firm is more likely to prescribe *that* pharmaceutical firm's drugs. Because this level of analysis exploits *within-doctor* variation, it has the advantage of controlling for unobservable doctor characteristics with doctor fixed effects.

We begin by forming (Doctor, Firm) pairs, or approximately 334,086 doctors x 12 firms ≈ 4 million observations. With this unit of observation, we estimate variants of the following model:

$$Claims_{i,j} = \alpha + \beta * Payments_{i,j} + \gamma * Controls_{i,j} + \varepsilon_{i,j} \qquad (2)$$

where *Claims* is a measure of the number of Medicare-reimbursed prescriptions written by physician i, for drugs marketed by pharmaceutical firm j. *Payments* measures the dollar value of transfers from pharmaceutical firm j to physician i, in the form of gifts, meals, travel, consulting, research, and speaking fees. *Payments* are observed in years 2009 through 2011, and *Claims* in 2010.[4]

Table 5 shows the results of estimating Equation (2), with Panels A and B corresponding to alternative ways of measuring the dependent variable, *Claims*. In the top panel (A), we use a discrete specification, whereby *Claims* takes a value of one if physician i prescribes one or more of pharmaceutical firm j's drugs at least fifty times in 2010, and zero otherwise. By focusing on a

[4] Note that, while we have three years of Payments, the conditional probabilities that physician *i* receives a payment from firm *j* are quite persistent over time. Table 4 calculates, for each pharmaceutical firm, the probability of payment in year *t+1* as a function of payment in year *t*. For example, the probability of payment by Merck for a doctor in 2010 is 80.3% if she was also paid in 2009 and 0.1% if she was not. Without exception, this relationship holds for every drug company in every year in which the calculation can be made. For this reason, it makes little difference in the regression analysis whether we define Payments for a specific year or as the sum across all three years.

relatively low threshold,[5] this approach is most useful for inferring the effects of pharmaceutical payments on the extensive margin of prescriptions. In contrast, Panel (B) measures *Claims* continuously, and thus attempts to explain the variation in prescriptions among doctors actively prescribing a given pharmaceutical firm's drugs.[6] Effects here inform us mostly about the intensive margin.

Consider first the results in Panel A. The estimated coefficient of 0.0274 (p<0.001) in the first column indicates that, roughly speaking, doubling the amount a drug company pays to a doctor increases by about 2.7% the likelihood that at least one of its drugs are prescribed a minimum of fifty times in 2010. Alternatively, in the second column, we see that that doctors who were paid *any* amount by a pharmaceutical firm in 2009 are over 22% more likely to prescribe at least 50 of its drugs in 2010. Given an average value for the dependent variable of 0.13 in 2009, this suggests a very strong association between firm-specific transfers to physicians and prescribing behavior.

The next pair of columns report the results of similar tests, the only difference being that *Payments* are measured in 2010, the same year that we observe prescription data. Comparing the fourth column to the second, the magnitude is a bit smaller (0.156, p<0.001), but still indicative of large effects. A doctor receiving payments from a pharmaceutical firm is over twice as likely to actively prescribe its drugs, compared to doctors not receiving any transfers. When we measure 2010 *Payments* continuously in column 3, we observe a nearly identical coefficient (0.0281, p<0.001) to that observed for 2009 *Payments*.

In columns five and six, we attempt to explain the cross-section of prescribing behavior in 2010 using data on pharmaceutical payments in 2011. While at first it may seem

[5] The threshold of fifty is necessary because ProPublica only lists specific drugs that a doctor prescribes at least fifty times.

[6] For further discussion of this "two-part model" see Mullahy (1998). We rely on linear regression models for consistency and ease of interpretation throughout the analysis. Our primary results are robust to alternative estimation methods including conditional logit models.

counterintuitive to link current prescriptions to future payments, there is a high degree of persistence in payments within doctor-firm pairs (Table 4). In our context, what this means is that payments in 2011 may simply proxy for payments in prior years. Since the pharmaceutical firms successively increased reporting of payments in each year, the advantage of restricting attention to 2011 payments is that bias due to sample selection, if any exists, may be reduced. Indeed, columns five and six indicate, respectively, effects for the continuous and discrete specification comparable to those observed in the first four columns.

Given the similarities across the first six columns, it is perhaps unsurprising that the marginal effect of *Payments* aggregated across years 2009-2011, shown in columns seven and eight, gives similar magnitudes. Moreover, in column nine, we split *Payments* in any year from 2009-2011 into *Big* (>$1000) and *Small* ($\leq$ $1000). As seen, payments in excess of $1000 are associated with an effect on prescriptions roughly twice as large, 0.207 (p<0.001) versus 0.0946 (p<0.001).

The final two columns present results when we incorporate a fixed effect for each of the over 334,086 physicians in our dataset. Here, differences in prescribing tendencies across physicians are removed by the fixed effects, so that the effects of industry payments are identified within individual providers. More specifically, given that there are multiple observations for each of physician, the coefficients on *Big Payments* and *Small Payments* are estimated by comparing a given doctor's tendency to prescribe drug company A's drugs versus those of drug company B, provided that one pays and one does not. As seen, not only are the coefficients nearly identical in magnitude, but the adjusted R^2 remains almost unchanged, suggesting that conditional on specialty, doctor-specific variation is not important.

Panel B shows the results when Equation (2) is re-estimated, but with two differences. First, the left hand side is the number of prescriptions filled for firm *j*'s drugs, written by doctor *i*. Second, the sample includes only (Doctor, Firm) pairs associated with at least fifty

prescriptions, the minimum required for ProPublica to report. This specification has the advantage of being able to relate changes in industry payments to the actual number of prescriptions written.

The columns are organized identically to Panel A, with 2009, 2010, 2011, and 2009-2011 aggregated shown in the first, second, third, and fourth pairs of columns. Roughly speaking, a 100% increase in the amount paid from a drug company to a physician increases by 7-10 the number of prescriptions we observe. The last column, which includes doctor fixed effects, again finds sharp differences in prescribing behavior depending on whether payments were large or small. Small payments correspond to an additional 10 prescriptions while big payments correspond to an additional 95 prescriptions.

IV. Mechanism

This section takes as given the association between industry payments and firm-specific prescription rates, and attempts to be more specific about the mechanism. We explore three alternatives. Although not mutually exclusive, these alternatives give differential predictions in a number of specific settings, which allows some measure of distinction between them.

First, we consider in Section A the possibility that pharmaceutical payments reflect compensation for a doctor's advice, perhaps about a certain disease or drug class. There is also the possibility that information runs in the opposite direction. More specifically, drug companies may use meetings with physicians to convey information, or perhaps merely the perception of information, about their products. We consider the implications of such pharmaceutical "detailing" in Section B. The final possibility is perhaps the simplest yet most cynical: payments from drug companies are valued strictly for their pecuniary benefit, apart from any information effects. Section C considers this possibility in more detail.

A. Paying for a doctor's expertise

Doctors likely represent a source of important information for pharmaceutical firms. In some cases, physicians are particularly knowledgeable about certain diseases or conditions, and therefore, may be in a position to lend expertise. In others, even when a physician isn't an expert, his or her experience prescribing one of the firm's drugs may nevertheless be valuable, e.g., reporting side effects or patient compliance. Importantly, payments from pharmaceutical firms in such cases need not alter the physician's subsequent prescribing behavior.

This is undoubtedly part of the story, particularly for physicians compensated for research activities. However, these are exceptional cases, comprising only 1.3% of the payment observations reported by ProPublica. In this section, we focus on situations where a doctor's expertise is unlikely to be the primary motive for a pharmaceutical firm and doctor interaction.

Our first test uses each doctor's prescribing behavior to infer his or her area of expertise. We begin by identifying for each doctor his or her most frequently prescribed drugs. For example, suppose a given doctor (Dr. X) is an ophthalmologist specializing in glaucoma, often writing prescriptions for Allergan's Lumigan and Pfizer's Xalatan, eye drops appropriate for this condition. We re-estimate equation (2), but exclude these frequently prescribed drugs when calculating the left hand side variable. That is, when summing Dr. X's prescriptions for Allergan, we ignore those for Lumigan, and likewise, those for Xalatan when making the same calculation for Pfizer. This exclusion means that any association between Dr. X's prescriptions and the payments of a given drug company are identified from drugs more likely to fall outside his area of expertise.

Columns 1 and 2 of Table 6 show the results of the discrete specification, but excluding the most frequently prescribed drugs when constructing the left hand side indicator variable. The coefficient on the *Big Payment* indicator is 0.113 ($p<0.001$) when the top five are excluded,

and 0.0721 ($p<0.001$) when drugs only outside each provider's top ten are considered. Compared to the last two columns in Table 5, the magnitude on the *Big Payment* indicator is cut by about half, revealing that although part of the big payment effect likely reflects doctor expertise, the impact of large transfers is not limited to these situations.

On the other hand, the impact of small payments on prescription probabilities is comparable between Tables 5 and 6, with only a small reduction in magnitude. Whereas the full sample indicates that small payments increase prescription probabilities by 8-9%, Table 6 indicates extensive margin effects of 7.7% ($p<0.001$) and 6.4% ($p<0.001$) for drugs outside the top five and ten, respectively. Given that small payments are less likely to reflect compensation for research activities or other indicators of expertise, this is perhaps expected.

Examining the continuous specification yields similar conclusions, shown in the fourth and fifth columns. For big payments, we observe an increase in prescriptions of about 62 ($p<0.001$) and 46 ($p<0.001$) for drugs outside a provider's top five and ten, respectively, again roughly half what we observe in the full sample. Small payments are associated with an increase of 7.6 ($p<0.001$) and 5.6 ($p<0.001$) in prescriptions, respectively, again outside each provider's top five and ten.

Another way to gauge a provider's expertise is to examine the types of activities around which he engages with drug companies. The types of activities listed by ProPublica allow us to identify situations where doctors are more likely to be retained due to their expertise. More specifically, if a doctor is enlisted for his or her expertise, payments for meals in isolation from other activities such as "research," "consulting," "speaking," and "travel" are unlikely. Consequently, by throwing out all (Doctor, Firm) pairs where at least one of these activities is also listed, we identify effects based on relationships involving only dinner, but nothing more.

The third and sixth columns show the results. In the discrete specification (column three), the coefficient on *Only Meals* is 0.0596 ($p<0.001$), indicating that doctors receiving

payment only in the form of meals are about 6% more likely to prescribe (at least fifty of) the paying firm's drugs. Although about one third smaller than in the full sample compared to the *Small Payment* indicator, recall from Table 2 that the unconditional mean of the *Any Payment* indicator variable is 0.10, so that the extensive margin effect of meal payments represents an increase of over fifty percent. The continuous specification indicates an intensive margin impact of 15.61 ($p<0.001$) prescriptions for meals which, coincidentally, is exactly the magnitude of the *Small Payment* indicator observed in the full sample.

B. Advertising

While access to expert physicians might represent one motivation for drug companies interacting with doctors, providing information may be another. The precise type of information conveyed might range considerably, including news about recently approved drugs, new applications for existing drugs, or the results of clinical studies. In these or similar cases, if a doctor becomes better informed about the firm's products via pharm, he or she may be more likely to prescribe them to patients. Of course, it is not strictly necessary for pharmaceutical detailing to contain genuine information to be effective, as long as a doctor *believes* it does.

In this section, we attempt to better understand whether the positive cross-sectional correlation between payments and prescriptions reflects information flow from drug companies. Our empirical strategy is to examine specific situations where information asymmetry between firms and doctors, or at least physicians' perception of this deficit, should be very small. One of these comparisons involves close substitutes, and three of them perfect substitutes between branded drugs and their generic equivalents. In all cases, the relevant drugs had been available for several years. Together, these factors should level the information playing field between doctors and physicians, making information flow from firms to doctors an unlikely explanation.

Our first comparison involves cholesterol-reducing drugs in the "statin" class. High cholesterol is one of the most commonly treated medical conditions among Medicare patients in the U.S. Accordingly, statins were the single most widely prescribed class of medications in 2010, with over 255 million prescriptions, involving both branded and generic alternatives. The two largest branded statins in 2010, by far, were Pfizer's Lipitor (atorvastatin) and AstraZeneca's Crestor (rosuvastatin), with combined sales over $11 billion. Lipitor is the highest selling prescription drug of all time, with sales exceeding $7 billion in 2010 alone. Crestor's sales accounted for almost $4 billion that year, sufficient to make it the eighth highest selling branded drug (in dollars). Among generics, simvastatin (formerly Merck's Zocor) is the most frequently prescribed drug in our Medicare dataset, with over 38 million prescriptions in 2010.

In addition to their ubiquity, two features of statin-class drugs are convenient for our purpose. First, although not identical, all statins share the same mechanism of action, and consequently, have comparable efficacy. Statins lower serum cholesterol levels, an important risk factor for coronary artery disease, by inhibiting HMG-CoA reductase, a catalyst in the biosynthesis of cholesterol (Istvan and Deisenhofer 2001).

Second, by 2010, statins were a well-established drug class.[7] Mevastatin, the first of the statins to be isolated, was studied and developed beginning in the early 1970s, and lovastatin (formerly Mevacor) was the first statin to be approved by the FDA, in 1987 (Endo 2004). Although some evidence suggests that rosuvastatin (Crestor) is somewhat more efficacious at reducing low-density lipoprotein cholesterol than atorvastatin (Lipitor) or simvastatin for equal doses (Jones et al. 2003), meta-analyses also suggest that the efficacy of each drug increases similarly with higher doses (Nicholls et al. 2010).

Given the chemical similarity and the extensive experience doctors had with statins, we proceed under the idea that payments from particular manufacturers are unlikely to represent

[7] A PubMed (http://www.ncbi.nlm.nih.gov/pubmed) search for the keyword "statin" yields 24,981 publications through the end of 2010.

(at least significant) opportunities to educate doctors about these drugs. We first compare prescriptions between Crestor and Lipitor, and then consider the implications for prescriptions of the generic alternative simvastatin.

The first two columns of Table 7 show the results of the Crestor-Lipitor comparison. About 10% of doctors in our sample (roughly 33,000) prescribed both drugs at least fifty times in 2010, a requirement for us to conduct a head-to-head analysis. We estimate the following regression:

$$\left(\frac{Cres-Lip}{Total}\right)_i = \alpha + \beta_1 * AstraPayment_i + \beta_2 * PfizerPayment_i + \gamma * Controls_i + \varepsilon_i \quad (3)$$

where *Cres* is the number of prescriptions written by doctor *i* for Crestor, *Lip* for Lipitor. The coefficient *β1* (*β2*) tells us whether the Crestor-Lipitor difference, scaled by *Total* (the number of total claims for doctor *i*) is influenced by payments from AstraZeneca (Pfizer).

As shown in the first column of Table 7, we estimate significant effects for both coefficients. The AstraZeneca coefficient is 0.00180 ($p<0.001$), indicating that a payment increases the fraction of Crestor prescribed, while the Pfizer coefficient is -0.00053 ($p<0.001$), resulting in comparatively more prescriptions for Lipitor. In the second column, we break these payments, as we have done in previous tables, into large (>$1000) and small. In both cases, the signs are preserved, and we continue to observe statistical significance. A big payment by AstraZeneca increases the scaled Crestor-Lipitor difference by 0.0143 ($p<0.001$), whereas a small payment matters about one-tenth as much. Likewise, large transfers from Pfizer matter approximately four times as much as smaller ones, although both are statistically significant at better than the one percent level. The fact that payments from *both* firms yield statistically significant effects indicates that regardless of which statin is preferred under the available evidence in 2010, the observed associations cannot be entirely explained by informative advertising.

Although the first two columns indicate that payments from pharmaceutical firms appear to induce substitution between brand names, the same effect might be observed between brand names and generics. In the third column, we explore whether combined payments from AstraZeneca and Pfizer influence the relative ratio of branded statins (i.e., Crestor plus Lipitor) versus the generic alternative simvastatin. To test for this effect, we estimate:

$$\left(\frac{Cres+Lip-Sim}{Total}\right)_i = \alpha + \beta_1 * AstraPayment_i + \beta_2 * PfizerPayment_i + \gamma * Controls_i + \varepsilon_i \quad (4)$$

where the only change is that the dependent variable is the difference between summed prescriptions of Lipitor and Crestor and simvastatin (*Sim*). As in previous tables, we include state and specialty fixed effects. The third column indicates that payment from either AstraZeneca or Pfizer increases the scaled difference between branded and generic statins. In the fourth and fifth columns, we break this up by firm, both of which are shown to have a positive effect. In each case, large payments matter considerably more than small payments.

To get a sense for the magnitude of wealth transfers in Table 7, we can use the table's coefficient estimates and the retail cost of statin drugs to estimate prescription behavior with and without payment. This approach is conservative because it attributes all of AstraZeneca's and Pfizer's payments to just these two drugs and only considers doctors who wrote 50 or more prescriptions for the drugs. Nevertheless, in 2010 the average retail cost of simvastatin (40 mg) was $68 while the cost for Crestor (40 mg) and Lipitor (40 mg) were $162 and$165, respectively (Consumer Reports Health 2010).[8] Thus, the per-prescription cost difference between brand-names (taking the simple average of Crestor and Lipitor costs) and generic simvastatin (assuming all 30-day prescriptions and their equivalence to monthly costs) was $95.50. Eliminating payments from Pfizer and AstraZeneca, i.e. setting the *Payment Indicator* to zero in the third column of Table 7 for the 64.47% of doctors who were paid, would have shifted

[8] Average costs for 20 mg doses were very similar, at $70 (simvastatin), $164 (Crestor), and $161 (Lipitor).

approximately 17 prescriptions per doctor, and 995,096 prescriptions in total, from Crestor and Lipitor to simvastatin.

According to this back-of-the-envelope exercise, therefore, eliminating payment-induced brand-name prescriptions would have reduced total expenditures by $94.8 million, or $1,624 per paid-doctor. In 2011, reported payments from AstraZeneca and Pfizer to providers totaled $308.48 million, so a sizeable portion of total provider payments would have been returned from shifts in prescriptions for just these two drugs among our sample of Medicare doctors. The per-doctor expenditure shift is also worth several large meals or gifts.

Although drugs within the class of statins are plausible substitutes, they are not chemically identical. Thus the possibility remains that the positive correlation between payments and prescriptions for statins is driven by beliefs – rather than incentives – of physicians. Put differently, although genuine information is unlikely to explain the patterns observed in Table 7, doctors may nevertheless be persuaded by pharmaceutical firms. The analysis in this section, because it considers identical chemicals, rules out even uninformed persuasion.

We consider the case of drugs whose name-brand and generic equivalent are both heavily prescribed in our 2010 sample. This is a unique phenomenon. We observe very few Medicare claims for off-patent name-brand drugs because insurance companies rarely cover name-brand drugs which have available generic equivalents. In fact, we find only five cases in which both a name-brand drug and its generic equivalent had at least 50 claims by at least 1,000 providers. Those drugs (and their generic equivalents) are AstraZeneca's Arimidex (anastrozole), Merck's Cozaar (losartan potassium), Pfizer's Dilantin (phenytoin), GlaxoSmithKline's Lanoxin (digoxin) and Pfizer's Protonix (pantoprazole). We remove Dilantin

and Lanoxin from the analysis because of concerns that the generic and name-brand are not chemically identical.[9]

We observe heavy volume for each of the three remaining drugs because of changes in the drug's exclusivity during 2010. Merck's patent for high blood pressure drug Cozaar expired in April (Doherty 2010), and AstraZeneca's patent for cancer drug Arimidex expired in June (Connolly 2010). In the case of Pfizer's Protonix, generic manufacturers were ordered by a US federal court in April to stop selling their generic version of Pfizer's drug due to patent infringement (Pearson, Decker, and Voreacos 2010). Patent expiration and court orders are plausibly unrelated to a doctor's belief about a particular drug's efficacy. For this reason, these three drugs provide a natural setting for identifying the incentive effects of payment behavior apart from beliefs.

We begin by considering the subset of doctors who prescribed either the name-brand or the generic equivalent. For example, there were a total of 2,361 doctors who prescribed the cancer drug Arimidex or its generic equivalent, anastrozole. For each of these 2,361 doctors we create a binary variable called *Name-Brand Indicator* which takes the value of one if a doctor prescribed the name brand drug in favor of the generic equivalent (in the case where he prescribes both, a value of 1 is assigned to the drug with the most prescriptions). Then we regress *Name-Brand Indicator* on *Big Payment Indicator* and *Small Payment Indicator* in the first column of Table 8.

The positive coefficients on both *Big Payment Indicator* and *Small Payment Indicator* demonstrate a positive relationship between payments from AstraZeneca and prescriptions of Arimidex. Unconditionally, there is a 79% probability that name-brand Arimidex is prescribed

[9] Dilantin is an epilepsy drug whose users have reported increases in seizures after switching to generic versions (http://www.webmd.com/epilepsy/news/20041025/generic-epilepsy-drugs-not-same), while Lanoxin had well-publicized recalls of its generics between 2008 and 2010 (http://www.fda.gov/Safety/Recalls/ArchiveRecalls/ucm150734.htm and https://www.mediguard.org/alerts/alert/940.html).

more frequently than its generic equivalent. However, this probability increases to 81% if a doctor received a small payment from AstraZeneca and to 98% if a doctor received a big payment from AstraZeneca. While the coefficient on *Small Payment Indicator* is insignificant, the coefficient on *Big Payment Indicator* is significant at the 1% level.

Columns 2 and 3 repeat the analysis for Merck's Cozaar and Pfizer's Protonix. In the case of Cozaar we can only estimate a coefficient on *Big Payment Indicator* because Merck reported only speaking fees (and not the less lucrative meals and gifts) between 2009 and 2011 (see Table 1). The coefficient is positive but indistinguishable from zero. In the case of Pfizer's Protonix the coefficient of 0.116 on *Big Payment Indicator* suggests that the probability of prescribing the name brand in favor of the generic increases from 42.2% to 53.6% if a doctor received a big payment from Pfizer.

Column 4 combines the observations from the first three columns and finds that the average increase in the probability of prescribing the name brand is 10.6% (p-value < 0.01) when *Big Payment Indicator* = 1. We find no effect for *Small Payment Indicator*. The final column includes state and specialty fixed effects with little change in the variables of interest.

C. Rent-seeking

The final explanation involves physicians altering their behavior in exchange for current, or expected, financial benefits from pharmaceutical firms. Unlike the previous alternatives involving information flow, this possibility is less capable of improving decision making, and indeed, may worsen outcomes for patients. For example, financial conflicts of interest may lead doctors to substitute a slightly inferior drug for another, or, as seen in the last section, increase costs via reluctance to prescribe generic alternatives.

In this section, we develop two empirical proxies for the tendency of physicians to engage in rent-seeking behavior. One is predominantly environmental, and the other genetic. As we will see, both cut the data in the way that suggests rent seeking is an important determinant of the empirical patterns we observe.

The first source of variation is motivated by Glaeser and Saks' (2006) study of corruption across U.S. states. They use conviction rates for corruption-related crimes, such as obstruction of justice, fraud, and election irregularities to proxy for state-level rates of corruption more generally. Our idea is that doctors living in more corrupt regions may, themselves, be more sensitive to the payments of drug companies when making prescription decisions.

In Figure 3, we plot the payment-prescription coefficient for each state on the y-axis, as a function of Glaeser and Saks' measure of political corruption on the x-axis, shown as percentiles. States with low levels of corruption are shown toward the left, and include Oregon (50th highest or 2nd percentile), Vermont (6th percentile), and Minnesota (8th percentile). At the other end are high-corruption states: Illinois (88th percentile), Louisiana (96% percentile), and Mississippi (98th percentile).

For each state, we run regression (2), using the same control variables (e.g., doctor specialty, pharmaceutical firm fixed effects, etc.) from Table 5, Panel B. The coefficient of interest is on the *Any_payment* dummy variable, interpreted as the additional prescriptions the typical doctor prescribes for a given drug company's products, conditional on him receiving a payment from that company. Because states vary so widely in the number of doctors, we scale each point estimate by the standard error of the estimated coefficient, so that a circle with twice the diameter of another is estimated twice as precisely.

Visual inspection reveals an upward sloping relation between prescription sensitivities to payments across states and convictions for corruption related crimes. Of the ten least corrupt states, eight have estimated sensitivities below 20, with only three states below the median

corruption level exceeding 25. On the other hand, almost two-thirds of states above the median are associated with coefficients above 25, with seven exceeding 35. Interestingly, the one notable outlier, Alaska, is associated with the highest per-capita conviction rate, and also the only negative estimated prescription-payment sensitivity. However, with only 253 Alaskan doctors entering the estimation, this is not statistically significant.

In Table 9, we formalize these comparisons in regressions. The first three columns show the results of estimating Equation (2) by corruption tercile, progressing from least to most corrupt. Confirming the graphical evidence shown in Figure 3, the first column indicates a point estimate of 20.35 prescriptions ($p<0.001$) for the least corrupt third of U.S. states. The coefficient increases by almost half in the second column to 29.06 ($p<0.001$), and by another ten percent for the most corrupt states (32.13, $p<0.001$). The fourth column aggregates all states together, and interacts the numerical value of the Glaeser-Saks corruption index percentiles, the same numbers displayed the x-axis of Figure 3. The *t*-statistic on the interaction is -7.04, indicating a steeply declining impact for drug company payments in less corrupt states.

In light of these findings, it is worth revisiting the heat maps shown in Figure 1. Note that both payments and prescription rate of branded drugs are heavily concentrated in the greater southeast region of the U.S. Focusing on Panel B, note that gulf coast states Texas, Louisiana, Mississippi, Alabama, and Florida, as well as neighbors Georgia and South Carolina – all above median rates of corruption – have significantly elevated prescription rates of branded drugs. States with high branded rates in different regions include New York (7th most corrupt state), New Jersey (17th), and Alaska (1st).

Combining all three heat maps, a coherent picture emerges: doctors in corrupt states are most sensitive to payments (Figure 3), pharmaceuticals disproportionately target these regions (Figure 1A), and the distribution of branded drugs reflects the combination of these effects (Figure 1B).

What these graphical patterns cannot tell us, however, is *why* – i.e., what is it about certain regions that fosters corrupt activity across very different areas, ranging from corrupt elected officials to rent seeking physicians? Manski's (1993) discussion of the "reflection problem" in social effects provides a useful context. *Endogenous* effects refer to classic "peer effects," such as a teenager going to the beach because (and only because) her friends are also going. *Exogenous* effects refer to common characteristics that lead groups to behave similarly, e.g., a group of fair-skinned teenagers avoiding the beach together for common fear of sunburn. *Correlated* effects refer to operating under a common environment, such as news of a shark attack inducing a "correlated" response by those living nearby.

Any of these seem plausible on our setting, and we see little way to convincingly distinguish between them. For example, there are considerable demographic differences between states, some of which reflect exogenous attributes, and others of which reflect common environmental influences. Poverty and education rates also differ considerably between states, both of which are positively related to corruption (Berkowitz and Clay 2004). There is also the possibility that corruption reflects social norms, being more tolerated in some regions than in others. This latter possibility corresponds to an endogenous effect, and is capable of explaining how corruption in two different arenas – i.e., politics and medicine – could be so strongly correlated within regions.

The only mechanism that probably can be excluded is cross-state differences in enforcement, a contextual factor often making causal inferences in corruption studies difficult. Two features of our setting make this less problematic. The first is a feature of Glaeser and Saks' measure of corruption itself. As the authors note, all convictions were prosecuted by the Federal Department of Justice, rather than local jurisdictions. Second, even were this not the case, receiving payments from drug companies is, in the vast majority of circumstances, not illegal, making its enforcement (or lack of enforcement) largely irrelevant.

The second cross-sectional proxy we use is physician gender. Studies of political corruption have found an inverse relationship between participation rates of females in government and political corruption (Dollar, Fisman, and Gatti 2001; Swamy et al. 2001). As with state-level variation, we explore whether groups (here defined by gender) more likely to exhibit corruption in one arena are likely to manifest it in another.

To investigate this issue, we use the database of Cong et al. (2011) which collects first names and self-identified genders from Facebook. For example, if an individual's first name is "Daniel" that person self-identifies as male 99.7% of the time, but if an individual's first name is "Stephanie" that person self-identifies as male 0.04% of the time. Some names are more ambiguous, such as "Blake" (87.4% male), "Pat" (45.8% male) and "Morgan" (39.8% male). From the database we create a *Male* dummy variable which takes the value one if the probability of male is at least 90% and takes the value of zero if the probability of male is less than 10%. For the ambiguous names (between 10% and 90%) the *Male* variable is assigned a missing value. According to this classification scheme, 71.7% of the doctors in our sample are male.

In the fifth column of Table 9, we estimate Equation (2) again, but only for the sample of physicians identified as females (*Male = 0*). Although statistically significant, the coefficient of 15.42 (p<0.001) is about half that observed for the full sample, and is roughly the magnitude observed for the least corrupt states such as Vermont, Washington, or Iowa. In the adjacent column, we estimate the same regression, but only for male physicians (*Male = 1*). The coefficient more than doubles to 32.23 (p<0.001), exceeded by only seven states, all ranking above the median level for corruption. The next column aggregates both males and females into a single specification, with the final column adding an interaction for state-level corruption; both coefficients remain highly significant.

We view the gender result as useful for both specific and general reasons. Specifically, it helps better identify the mechanism underlying the pay-prescription relation observed in our

sample of physicians. Whereas it makes little sense to think that information flow between firms and doctors would differ systematically across males and female physicians, studies from other settings (e.g., politics) suggest that gender differences in corruption *should* be expected. Further, the fact that this result survives, and indeed appears almost independent of, the effect of state-level corruption, lends further support to the idea that rent seeking by physicians is at least part of the story.

More generally, whether women appear to engage in less corruption (in any setting) is itself subject to multiple interpretations. For example, does this reflect differences in exogenous characteristics, such as an inherent distaste for corruption or dishonesty? Or, are institutional or contextual effects – such as women paying a higher price for getting caught – a more plausible explanation? While difficult to make these distinctions in studies of political corruption, the fact that tilting prescriptions toward friendly drug companies is neither illegal nor enforced suggests that the patterns observed likely reflect inherent differences in attitudes toward corruption between the sexes.

V. Conclusion

The ideal of healthcare provision is embodied in the Hippocratic Oath: "I will prescribe regimens for the good of my patients according to my ability and my judgment…" In this paper, we evaluate whether a physician's judgment about prescriptions is in part influenced by non-patient sources: those of large, well-financed pharmaceutical companies.

Using data from twelve drug companies, more than 330,000 physicians and nearly one billion prescriptions, we find that when a drug company pays a doctor he is more likely to prescribe that company's drugs. A payment from a pharmaceutical company corresponds to, on average, an additional 29 Medicare prescriptions per year, and this number rises to nearly 100 prescriptions if the payment is at least $1000. Our specifications are stringent, accounting for

pharmaceutical firm, state, specialty, and even physician fixed effects. At least some of the evidence reflects rent-seeking behavior on the part of doctors. For example, we find that pay matters for prescribing behavior even among drugs with identical, generic alternatives. Moreover, the pay-for-prescription sensitivity is greater for doctors among high-corruption states and for male doctors.

Whether these results are surprising likely depends on whether one views a physician – and her opinions – as sacrosanct. To a cynical reader perhaps the presence of influence is self-evident from payments: after all, if payments from firms to doctors did not change doctor behavior, why would profit-maximizing firms choose to make them in the first place? While this view seems sensible, it ignores the fact that payments may reflect (rather than cause) the opinions of physicians or represent valuable transfers of information from firms to doctors. Given that the balance of our evidence is best explained by either persuasive advertising from drug companies or rent-seeking behavior from doctors, to a less-cynical reader our findings should be a call to consider outside influences when taking in medical advice.

In the same way, our results have clear policy implications. If payment behavior simply reflects a doctor's already-held opinion, then mandatory disclosure of physician payments (as required by the 2014 Physician Payment Sunshine Act) would impose an unnecessary cost on the healthcare system. Instead, given our evidence that payments incentivize or persuade doctors to change their behavior, disclosure of these transfers will help patients to best interpret and understand the medical advice they receive.

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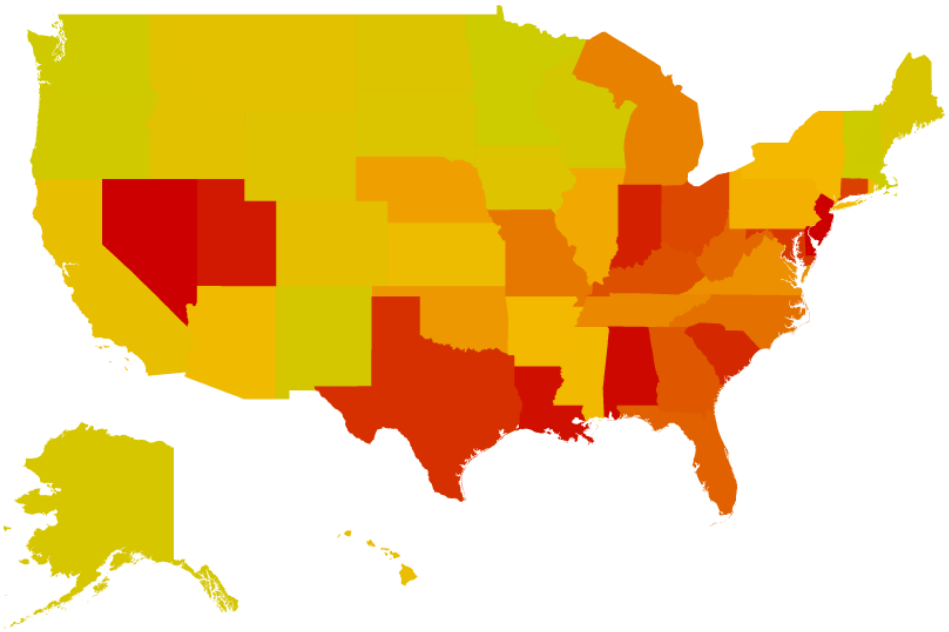
Figure 1: Payments and Prescriptions by State

Each panel provides a heat map by state where intensity runs from low (light green) to high (dark red). The top panel plots the percentage of doctors who receive a payment from any of the twelve pharmaceutical firms in our sample. The bottom panel plots the percentage of total prescriptions that were for drugs sold by our twelve pharmaceutical firms.

PANEL A: Percentage of Doctors Receiving Pharmaceutical Firm Payments



PANEL B: Percentage of Prescriptions for Pharmaceutical Firm Drugs

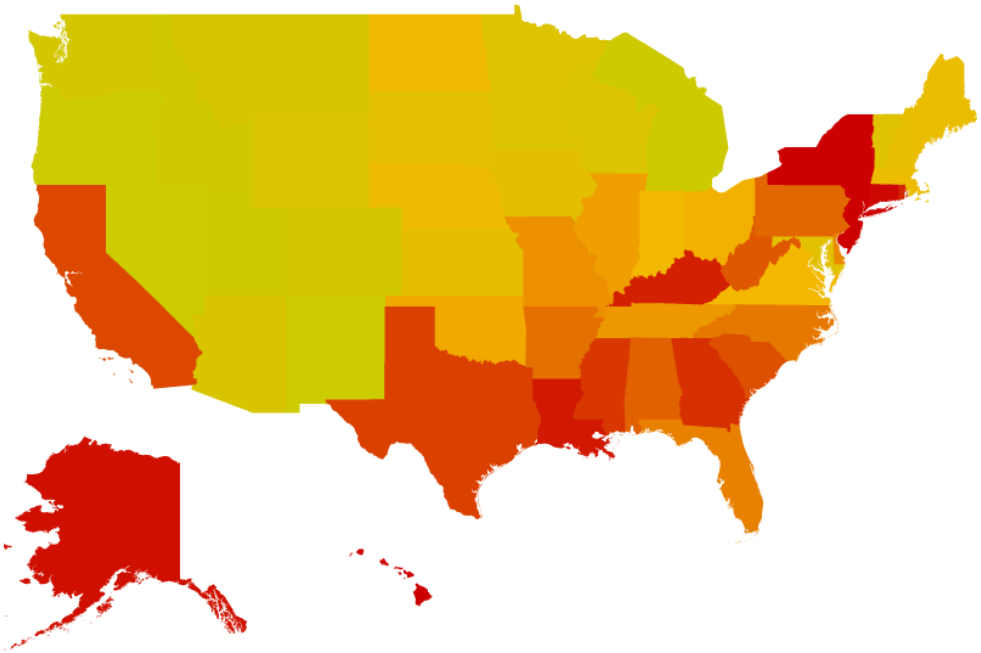
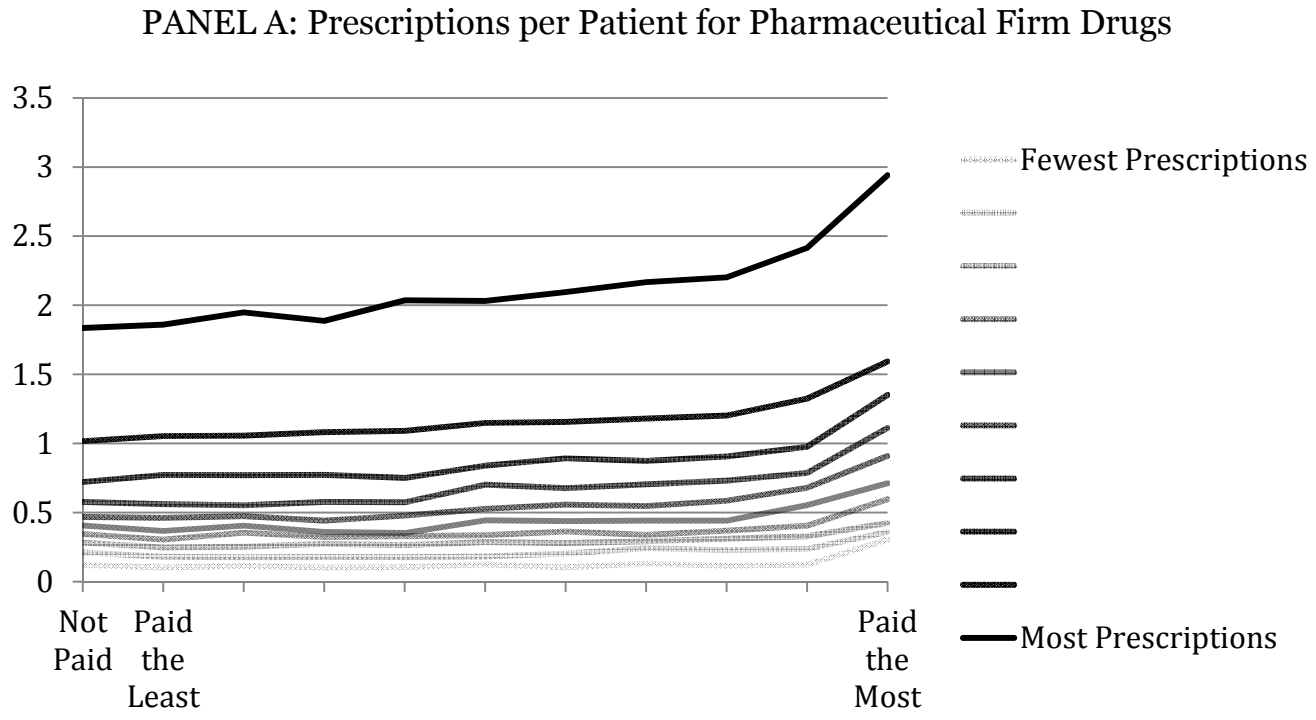


Figure 2: Payments and Prescriptions per Patient

The top panel plots prescriptions per patient for drugs of our twelve pharmaceutical firms. The bottom panel plots prescriptions per patient for drugs not from our twelve pharmaceutical firms. In both panels, doctors are first sorted into decile bins according to total prescriptions and then into decile bins according to total payments from our twelve pharmaceutical firms.



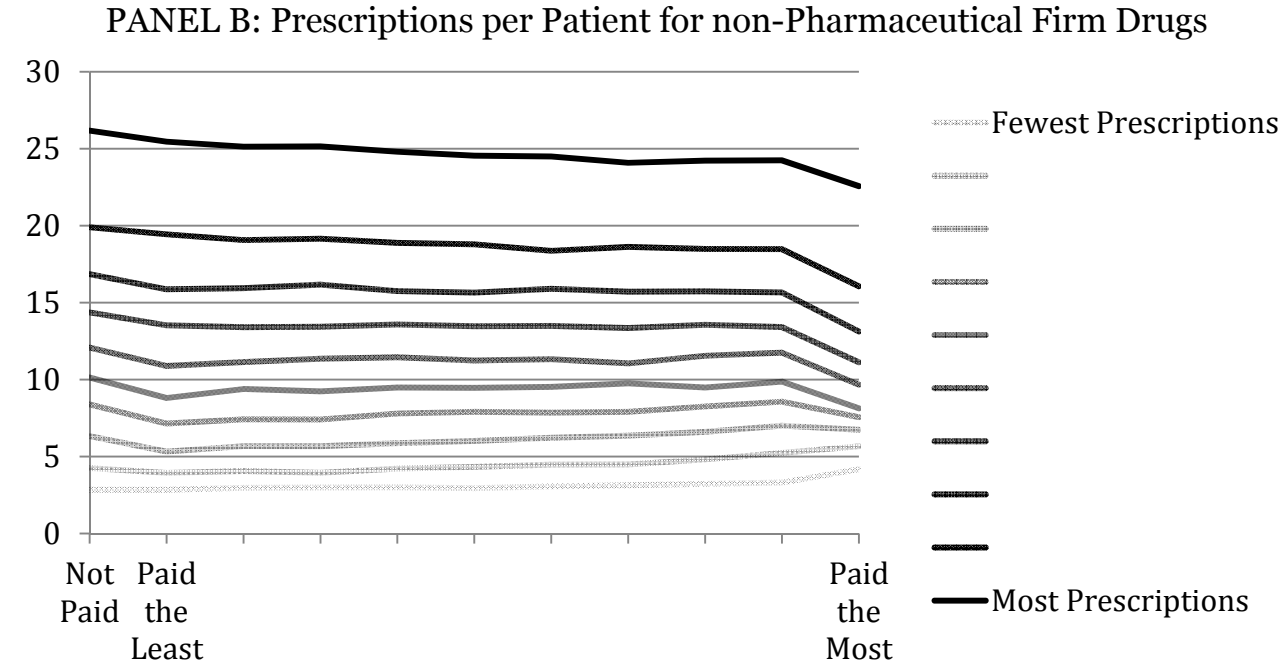


Figure 3: Payment/Prescription Sensitivity and State-Level Corruption

Each bubble in the plot corresponds to an individual state. On the x-axis is the state's per-capita measure of political corruption according to Glaeser and Saks (2006). On the y-axis is the state's coefficient from a regression of total prescriptions on payments. The size of each bubble represents the size of the standard error from these regression, with larger bubbles indicating more precise estimates.

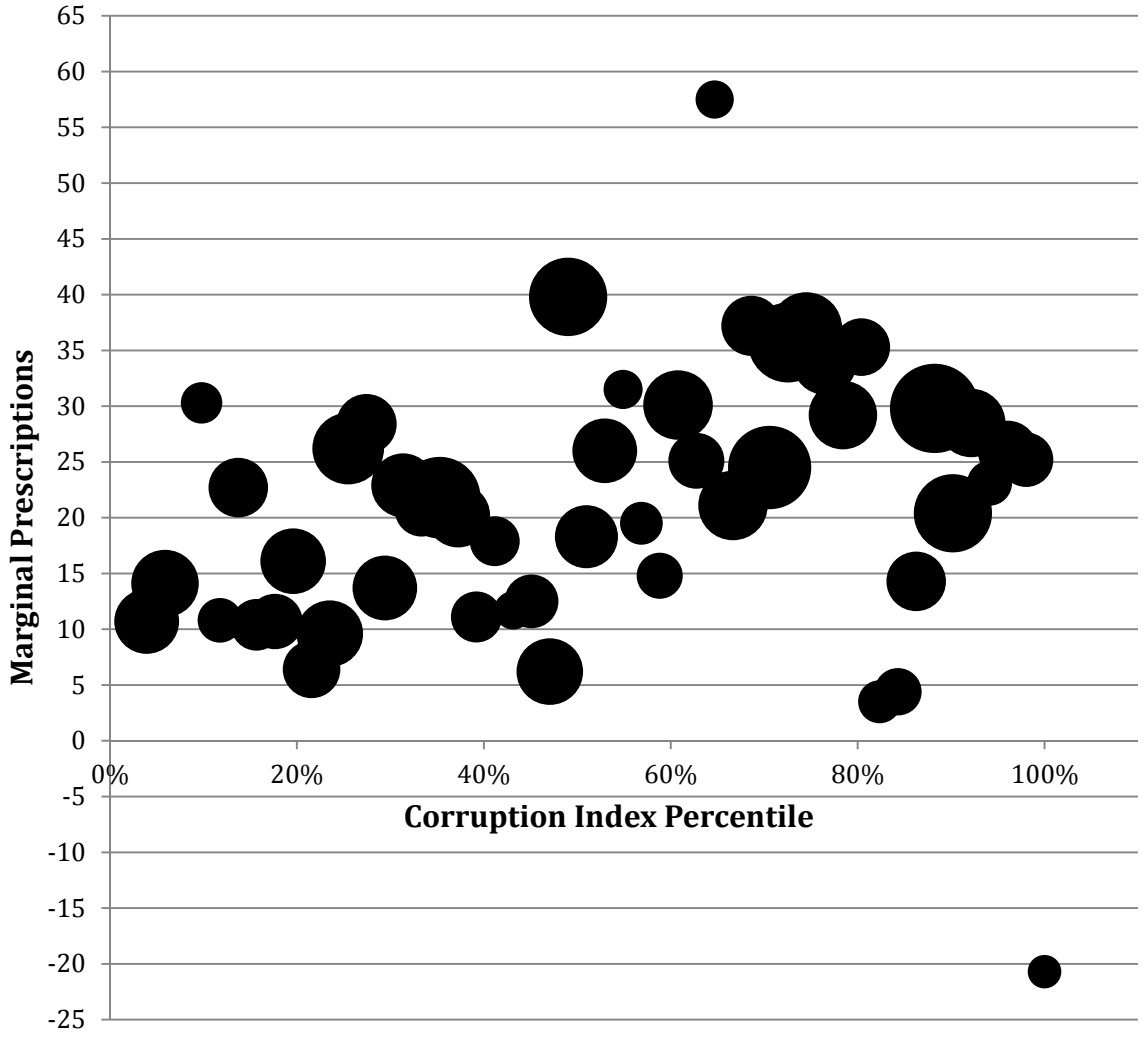


Table 1: Payments and Reporting Practices by Pharmaceutical Firms

The top panel describes the reporting practice for payments to healthcare providers by each of twelve pharmaceutical firms during the period 2009 - 2011. Data are taken from ProPublica's *Dollars for Docs* database (ProPublica 2013a). Reporting varies by year and categories reported. The top panel also includes the number of unique providers to whom payment was made as well as total dollars paid by year. The bottom panel provides summary statistics for the various payment categories.

PANEL A: Pharmaceutical Firms and Reporting Practices

	2009			2010			2011		
	Categories	Providers	Total $ Reported	Categories	Providers	Total $ Reported	Categories	Providers	Total $ Reported
Allergan	-	-	-	None Identified	41,528	-	Research, Gifts, Meals, Royalties, Speaking, Travel	42,572	-
AstraZeneca	-	-	-	Speaking	2,381	$31.47M	Consulting, Gifts, Meals, Research, Speaking, Travel	116,643	$114.21M
Cephalon	None Identified	935	$9.25M	Consulting, Gifts, Meals, Research, Speaking, Travel	45,575	$21.00M	Consulting, Gifts, Meals, Research, Speaking, Travel	36,157	$31.17M
Eli Lilly	Consulting, Speaking, Other	4,963	$82.09M	Consulting, Speaking, Travel, Other	4,875	$77.75M	Consulting, Meals, Research, Speaking, Travel, Other	101,898	$226.40M
EMD Serono	-	-	-	-	-	-	Consulting, Gifts, Meals, Speaking, Travel, Other	11,112	$1.85M
GlaxoSmithKline	Consulting, Speaking	5,716	$50.60M	Consulting, Speaking	5,249	$56.76M	Consulting, Research, Speaking	4,909	$120.82M
Johnson & Johnson	-	-	-	Combination, Consulting, Meals, Speaking, Travel, Other	2,166	$17.94M	Consulting, Meals, Speaking, Travel, Other	80,704	$22.96M
Merck	Speaking	1,640	$9.29M	Speaking	2,019	$20.00M	Speaking	2,454	$26.50M
Novartis	-	-	-	-	-	-	Speaking	3,259	$24.58M
Pfizer	Consulting, Gifts, Meals, Research, Speaking, Travel	4,738	$37.63M	Consulting, Gifts, Meals, Research, Speaking, Travel	196,453	$176.70M	Consulting, Gifts, Meals, Research, Speaking, Travel	161,025	$194.27M
Valeant	-	-	-	Consulting, Gifts, Meals, Other	6,136	$306.69K	Consulting, Expenses, Gifts, Meals, Speaking, Travel, Other	15,855	$1.50M
Viiv	-	-	-	Consulting, Research, Speaking	435	$7.84M	Consulting, Research, Speaking	524	$8.79M
All Pharmas		16,096	$188.86M		264,137	$409.78M		388,451	$773.05M

PANEL B: Payment Size by Type

	Observations	Mean	Standard Deviation	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile
Consulting	20,940	$4,205	$10,300	$75	$700	$2,000	$4,000	$13,647
Gifts/Items	102,423	$80	$580	$9	$45	$72	$99	$169
Meals	1,295,221	$74	$125	$11	$16	$37	$93	$239
Research	20,961	$51,262	$226,724	$675	$4,650	$14,631	$44,257	$183,550
Speaking	65,238	$9,969	$16,634	$700	$2,000	$4,500	$10,651	$41,900
Travel	34,849	$1,312	$2,647	$20	$104	$565	$1,294	$5,499
Other	90,991	$313	$2,461	$10	$12	$23	$58	$257

Table 2: Sample Summary Statistics

The table provides summary statistics by doctor in Panel A and by (Doctor, Firm) pair in Panel B. The set of doctors and Medicare Part D claims are taken from the ProPublica *Prescriber Checkup* database (ProPublica 2013b). Total payments are the sum of all payments between 2009 and 2011 from the ProPublica *Dollars for Docs* database (ProPublica 2013a). "Branded" claims are insurance claims for drugs marketed by our twelve pharmaceutical firms.

PANEL A: By Doctor

	Observations	Mean	Standard Deviation	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile
Total Payments	334,086	$2,108	$25,870	$0	$0	$14	$146	$1,701
Payment Indicator	334,086	0.58	0.49	0	0	1	1	1
Total Patients	334,086	217	177.18	51	105	174	280	519
Total Medicare Claims	334,086	2980	4,061	213	637	1,527	3,710	10,508
Total Branded Medicare Claims	334,086	192	439	0	0	55	203	851
Total Patients | Payment Indicator = 1	192,484	243	175	61	123	200	314	564
Total Medicare Claims | Payment Indicator = 1	192,484	3566	4,521	302	850	1,954	4,552	12,099
Total Branded Medicare Claims | Payment Indicator = 1	192,484	258	519	0	0	84	299	1,059

PANEL B: By (Doctor, Firm) Pair

	Observations	Mean	Standard Deviation	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile
Payment Indicator	4,009,032	0.11	0.31	0	0	0	0	1
Payment Size | Payment Indicator = 1	398,772	$1,766	$21,403	$11	$23	$57	$143	$3,378
Prescription Indicator	4,009,032	0.10	0.30	0	0	0	0	1
Prescriptions | Prescription Indicator = 1	398,515	161	183	52	65	102	185	451

Table 3: Payments and Prescription Rates for Physicians

The dependent variable is prescriptions per patient for drugs of our twelve pharmaceutical firms. *Log(Total Payments)* is the natural logarithm of total payments between 2009 and 2011 from our twelve pharmaceutical firms. *Residual Firm Prescriptions per Patient* are the prescriptions per patient for drugs not from our twelve pharmaceutical firms. *Paid Zero Indicator* is a binary variable which takes the value of one if a doctor was not paid. *Paid Decile = X Indicator* is a binary variable which takes the value of one is a doctor is in decile X of the payment distribution. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Pharmaceutical Firm Prescriptions per Patient					
Log(Total Payments)	0.0865***	0.0733***	0.0702***			
	(0.00137)	(0.00139)	(0.00137)			
Residual Prescriptions per Patient	0.0722***	0.0919***	0.0918***			
	(0.000529)	(0.000797)	(0.000799)			
Paid Zero Indicator				-0.151***	-0.156***	-0.150***
				(0.00705)	(0.00653)	(0.00653)
Paid Decile = 1 Indicator				-0.112***	-0.0810***	-0.0722***
				(0.00876)	(0.00799)	(0.00792)
Paid Decile = 2 Indicator				-0.0917***	-0.0690***	-0.0645***
				(0.00888)	(0.00813)	(0.00806)
Paid Decile = 3 Indicator				-0.0699***	-0.0464***	-0.0482***
				(0.00925)	(0.00848)	(0.00842)
Paid Decile = 4 Indicator				-0.0710***	-0.0441***	-0.0436***
				(0.00898)	(0.00825)	(0.00817)
Paid Decile = 6 Indicator				0.0412***	0.0415***	0.0395***
				(0.00980)	(0.00898)	(0.00889)
Paid Decile = 7 Indicator				0.0798***	0.0829***	0.0798***
				(0.00987)	(0.00910)	(0.00900)
Paid Decile = 8 Indicator				0.168***	0.169***	0.163***
				(0.0104)	(0.00964)	(0.00955)
Paid Decile = 9 Indicator				0.300***	0.295***	0.280***
				(0.0113)	(0.0106)	(0.0106)
Paid Decile = 10 Indicator				0.516***	0.412***	0.407***
				(0.0123)	(0.0119)	(0.0118)
Specialty Fixed Effects	NO	YES	YES	NO	YES	YES
State Fixed Effects	NO	NO	YES	NO	NO	YES
Non-Pharma 12 Decile Fixed Effects	NO	NO	NO	YES	YES	YES
Observations	179,432	179,432	179,432	334,086	334,086	334,086
Adjusted R^2	0.319	0.425	0.437	0.275	0.381	0.390

Table 4: Payments and Persistence

The table reports the likelihood of a doctor in our sample receiving a payment in a year as a function of the prior year for each pharmaceutical firm. The first two columns report the probability of a doctor receiving a payment in 2010 as a function of whether the doctor received a payment in 2009 (column 1) or whether the doctor received no payment in 2009 (column 2). The second two columns report the probability of a doctor receiving a payment in 2011 as a function of whether the doctor received a payment in 2010 (column 3) or whether the doctor received no payment in 2010 (column 4). Missing cells are for pharmaceutical firms that did not report in the prior year.

	Probability of 2010 Payment		Probability of 2011 Payment	
	Given 2009 Payment	Given No 2009 Payment	Given 2010 Payment	Given No 2010 Payment
Allergan	-	-	68.3%	2.0%
AstraZeneca	-	-	82.8%	24.6%
Cephalon	81.7%	8.7%	51.8%	2.7%
Eli Lilly	76.5%	0.1%	86.9%	21.6%
EMD Serono	-	-	-	-
GlaxoSmithKline	65.1%	0.3%	57.5%	0.3%
Johnson & Johnson	-	-	74.6%	15.1%
Merck	80.3%	0.1%	67.7%	0.2%
Novartis	-	-	61.1%	0.2%
Pfizer	90.7%	32.4%	62.6%	9.0%
Valeant	-	-	37.0%	0.9%
Viiv	-	-	69.4%	0.0%

Table 5: Payments and Prescription Behavior

The table relates payments made by pharmaceutical firms to prescribing behavior. The unit of observation is a (Doctor, Firm) pair. Panel A considers specifications where the dependent variable, *Prescription Indicator*, is binary and equals one if the doctor prescribes any of the pharmaceutical firm's drugs at least 50 times. Panel B's dependent variable is the total number of prescriptions in the (Doctor, Firm) pair given that *Prescription Indicator* = 1. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

PANEL A

	Dependent Variable: Prescription Indicator									
Log Payments 2009	0.0274***									
	(0.000500)									
Payment 2009 Indicator		0.227***								
		(0.00433)								
Log Payments 2010			0.0281***							
			(0.000249)							
Payment 2010 Indicator				0.156***						
				(0.00112)						
Log Payments 2011					0.0269***					
					(0.000177)					
Payment 2011 Indicator						0.129***				
						(0.000725)				
Log Total Payments							0.0270***			
							(0.000156)			
Any Payment Indicator								0.126***		
								(0.000674)		
Any Payment - Big									0.207***	0.207***
									(0.00277)	(0.00277)
Any Payment - Small									0.0946***	0.0893***
									(0.000697)	(0.000712)
Total Prescriptions	3.16e-05***	3.16e-05***	2.74e-05***	2.50e-05***	2.45e-05***	2.25e-05***	2.24e-05***	2.25e-05***	2.45e-05***	
	(1.60e-07)	(1.60e-07)	(1.04e-07)	(9.11e-08)	(9.13e-08)	(8.11e-08)	(8.11e-08)	(8.10e-08)	(9.14e-08)	
State Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	-
Specialty Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	-
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Doctor Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES
Observations	1,670,430	1,670,430	3,340,860	3,674,946	3,674,945	4,009,032	4,009,032	4,009,032	3,674,946	3,674,946
Adjusted R^2	0.321	0.320	0.300	0.287	0.299	0.287	0.288	0.288	0.299	0.308

PANEL B

	Dependent Variable: Total Prescriptions | Prescription Indicator = 1									
Log Payments 2009	9.882***									
	(0.356)									
Payment 2009 Indicator		86.45***								
		(3.257)								
Log Payments 2010			8.996***							
			(0.192)							
Payment 2010 Indicator				45.89***						
				(0.919)						
Log Payments 2011					6.989***					
					(0.151)					
Payment 2011 Indicator						28.62***				
						(0.646)				
Log Total Payments							7.176***			
							(0.137)			
Any Payment Indicator								28.93***		
								(0.621)		
Any Payment - Big									89.86***	95.05***
									(2.421)	(4.272)
Any Payment - Small									15.61***	10.63***
									(0.577)	(1.136)
Total Prescriptions	0.0184***	0.0184***	0.0174***	0.0170***	0.0173***	0.0169***	0.0169***	0.0169***	0.0173***	
	(0.000264)	(0.000264)	(0.000181)	(0.000186)	(0.000183)	(0.000188)	(0.000188)	(0.000188)	(0.000183)	
State Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	-
Specialty Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	-
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Doctor Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES
Observations	231,374	231,374	387,958	398,371	388,101	398,515	398,515	398,515	388,102	388,102
Adjusted R^2	0.367	0.367	0.361	0.329	0.358	0.326	0.329	0.326	0.360	0.304

Table 6: Specialization

Only Meal Payment Indicator takes the value of one for a (Doctor, Firm) pair if a doctor only received a meal as payment from a pharmaceutical firm. Columns 1 and 2 repeat the analysis of Panel A of Table 5 (Column 10) but restrict attention to only the drugs outside a doctor's top five and top ten most prescribed drugs. Similarly, Columns 4 and 5 repeat the analysis of Panel B of Table 5 (Column 10) but restrict attention to only the drugs outside a doctor's top five and top ten most prescribed drugs. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Prescription Indicator			Dependent Variable: Total Prescriptions | Prescription Indicator = 1		
	Outside Top 5	Outside Top 10		Outside Top 5	Outside Top 10	
Any Payment Indicator - Big	0.113***	0.0721***		62.25***	45.66***	
	(0.00237)	(0.00203)		(4.056)	(3.800)	
Any Payment Indicator - Small	0.0773***	0.0635***		7.612***	5.610***	
	(0.000645)	(0.000587)		(1.042)	(1.010)	
Only Meal Payment Indicator			0.0596***			15.61***
			(0.000814)			(1.998)
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Doctor Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	3,674,946	3,674,946	2,279,173	299,737	244,430	239,851
Adjusted R^2	0.786	0.795	0.532	0.326	0.347	0.214

Table 7: Statins

This table considers the case of two branded statin drugs and a within-class generic competitor: Crestor (rosuvastatin), Lipitor (atorvastatin), and simvastatin (formerly marketed as Zocor). The dependent variable is the difference in the number of prescriptions between Crestor (both branded drugs) and Lipitor (simvastatin), scaled by each doctor's total Medicare claims. Columns 1-2 consider only those doctors observed to have prescribed both Crestor and Lipitor while columns 3-5 consider only those doctors observed to have prescribed Crestor or Lipitor, and simvastatin. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable:				
	Crestor - Lipitor	Crestor - Lipitor	Crestor/Lipitor - simvastatin	Crestor/Lipitor - simvastatin	Crestor/Lipitor - simvastatin
Pfizer Payment Indicator	-0.000526***			0.00243***	
	(0.000181)			(0.000204)	
AstraZeneca Payment Indicator	0.00180***			0.000854***	
	(0.000177)			(0.000207)	
Pfizer Payment Indicator - Small		-0.000508***			0.00216***
		(0.000179)			(0.000204)
Pfizer Payment Indicator - Big		-0.00228***			0.0105***
		(0.000675)			(0.000840)
AstraZeneca Payment Indicator - Small		0.00152***			0.000553***
		(0.000175)			(0.000207)
AstraZeneca Payment Indicator - Big		0.0143***			0.0171***
		(0.00115)			(0.00139)
Astra or PfizerPayment Indicator			0.00230***		
			(0.000198)		
Specialty Fixed Effects	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES
Observations	32,860	32,860	90,559	90,559	90,559
Adjusted R^2	0.072	0.083	0.108	0.109	0.114

Table 8: Name-Brand vs. Generic Drugs

This table considers the case of three name-brand drugs and their generic equivalents: Arimidex (anastrozole), Cozaar (losartan potassium) and Protonix (pantoprazole). The dependent variable, *Name-Brand Indicator*, is a binary variable that takes the value of 1 if a doctor prescribes the name-brand instead of the generic (in the case where she prescribes both, a value of 1 is assigned to the drug with the most prescriptions). Column 1 (2, 3) considers only the set of doctors who prescribed Arimidex (Cozaar, Protonix) or its generic equivalent. Columns 4 and 5 combine all of the observations in the first three columns. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Name-Brand Indicator				
	Arimidex	Cozaar	Protonix	All	All
Payment Indicator - Big	0.190***	0.0273	0.116***	0.107***	0.0853***
	(0.00847)	(0.0307)	(0.0283)	(0.0233)	(0.0207)
Payment Indicator - Small	0.0217		-0.00757	-0.00345	0.00809
	(0.0173)		(0.00847)	(0.00767)	(0.00698)
Firm Fixed Effects	NO	NO	NO	YES	YES
Specialty Fixed Effects	NO	NO	NO	NO	YES
State Fixed Effects	NO	NO	NO	NO	YES
Observations	2,361	12,707	12,477	27,545	27,545
Adjusted R^2	0.002	0.000	0.001	0.294	0.400

Table 9: Rent-Seeking

The dependent variable is the total number of prescriptions in the (Doctor, Firm) pair given that *Prescription Indicator* = 1. Columns 1 (2, 3) consider the subset of states in the bottom (middle, top) tercile of the Glaeser and Saks (2006) corruption index. Columns 5 (6) consider the subset of doctors which have a female (male) first name. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Total Prescriptions | Prescription Indicator = 1							
	Low Corruption States	Medium Corruption States	High Corruption States	All	Females	Males	All	All
Any Payment Indicator	20.35***	29.06***	32.13***	21.28***	15.42***	32.25***	8.913***	0.650
	(1.147)	(1.151)	(0.909)	(1.232)	(1.200)	(0.777)	(1.167)	(1.588)
Any Payment Indicator * Corruption Index				0.136***				0.147***
				(0.0193)				(0.0204)
Male							-9.063***	-9.057***
							(0.688)	(0.689)
Any Payment Indicator * Male							24.69***	24.65***
							(1.341)	(1.343)
Total Prescriptions	0.0147***	0.0201***	0.0158***	0.0169***	0.0166***	0.0166***	0.0165***	0.0165***
	(0.000609)	(0.000349)	(0.000198)	(0.000188)	(0.000627)	(0.000217)	(0.000206)	(0.000206)
Specialty Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Pharma Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	83,737	132,883	181,895	397,894	79,886	262,519	342,405	341,882
Adjusted R^2	0.345	0.341	0.318	0.326	0.282	0.330	0.323	0.323