

MANDATORY DISCLOSURE: THEORY AND EVIDENCE FROM INDUSTRY-PHYSICIAN RELATIONSHIPS

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Abstract

The interaction of disclosure laws and the targeted behavior is typically unknown since data on disclosed activity rarely exist in the absence of disclosure laws. We exploit data from legal settlements disclosing \$316 million in pharmaceutical company payments to 316,622 physicians across the U.S. from 2009-2011. States were classified as having strong, weak, or no disclosure based on whether data were reported only to state authorities (weak) or were publicly available (strong). Strong disclosure law was associated with reduced payments among doctors accepting less than \$100 and increased payments among doctors accepting greater than \$100. Weak disclosure states, despite imposing administrative compliance costs to industry, were indistinguishable from no disclosure states. This result suggests that the primary mechanism for fewer small payments in strong disclosure states was physicians' reduced willingness to accept payments rather than the imposition of significant administrative costs on industry. We conduct additional analysis holding fixed the cost for pharmaceutical companies of disclosing data, which was possible because Massachusetts began releasing payment data online during our sample period. Differences-in-differences analyses and multiple regression yield similar estimates for each payment category: Mandatory disclosure reduced payments for speaking and for meals but increased payments for consulting activities. Differences-in-discontinuities in distribution of payments at the disclosure threshold among strong and weak disclosure states support the interpretation of physicians' reduced willingness to accept payments. Significant disclosure aversion reducing conflicts of interest is consistent with the policy goals of mandatory disclosure, though the increased payments among those receiving large payments may have been unintended.

Keywords: Physician Payment, Conflicts of Interest, Ethics

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1. INTRODUCTION

The relationship between the pharmaceutical industry and the medical profession is the subject of heated debate in both the U.S. and Europe (see, e.g., Article 94 of European Parliament and Council Directive 200/83/EC on the Community code relating to medicinal products for human use, as amended; German Supreme Court decisions in the cases 3 StR 458/10, 4 StR 239/03, and 1 Str 165/03). In recent years, professional organizations have produced policy recommendations to limit contact between physicians and the pharmaceutical industry (see, e.g., Articles 9-14 of the European Federation of Pharmaceutical Industries and Associations (EFPIA) Code on the Promotion of Prescription-Only Medicines to, and Interactions with, Healthcare Professionals; and various publications of the World Health Organization (WHO), including "Understanding and Responding to Pharmaceutical Promotion: A Practical Guide," 2011, aimed at healthcare professionals). A large body of research recently summarized by the World Health Organization suggests that physicians may be influenced by financial conflicts of interest (Norris et al. 2005); recommendations limiting the size of transactions between physicians and pharmaceutical companies have been adopted by professional and industry groups.

Spending by the pharmaceutical industry on promotions and marketing in the U.S. grew from \$11 billion in 1996 to an estimated \$29 billion in 2011 (Donohue et al. 2007), with other independent estimates placing the number much higher (Donohue et al. 2007, IMS Health 2011, Kerber 2004, Wolfe, 1996, Gagnon and Lexchin 2008). Even accounting for direct-to-consumer advertising, 90% of promotional expenditures are directed towards physicians, amounting to between \$30,000 and \$61,000 per physician each year (Donohue et al. 2007). Although direct payments to physicians appear to constitute a relatively small proportion of these promotional expenditures, they are the subject of professional and political controversy. There is concern that these transactions may create conflicts of interest that undermine clinical objectivity and public trust in physician recommendations (Wazana 2000, Studdert et al. 2004, Chimonas et al. 2007, Campbell 2007). Moreover, industry-physician relationships have been linked to medical research, discovery, and promulgation of new drugs (Cockburn and Henderson 1998, Chatterji et al. 2008, Zinner et al. 2009).

The prevailing strategy for addressing potential conflicts of interest has been enhancement and

enforcement of disclosure (Katz et al. 2003). This has been the case despite a lack of empirical evidence regarding the effects of disclosure on industry-physician financial relationships. Prior to federal legislation on disclosure in 2014, several states enacted “sunshine laws” that required companies to report payments to physicians (Brennan and Mello, 2007). In Massachusetts, Vermont, and Minnesota, these disclosures were public (Mass. Gen. Laws, ch. 111N, §6; Minn. Stat. §151.461; Vt. Stat. tit. 18, §§4631-2.) and since 2009, many pharmaceutical companies have publicly disclosed payment data for all 50 states (Merrill et al. 2013). Beginning in 2014, the Patient Protection and Affordable Care Act required disclosure of payments from pharmaceutical companies to physicians and the compilation of this data into a publicly searchable online database (42 C.F.R. §§ 402 and 403).

Critics of disclosure suggest that these laws stigmatize physicians who maintain collaborative relationships with industry that are essential to innovation and product feedback (Sade 2011, Sigworth et al. 2001, Santhakumar and Adashi 2015). Some contend that disclosure may have the unintended consequences of moral licensing among physicians to conduct themselves in a biased manner and/or of producing greater public trust in physicians who have received larger payments (Cain et al. 2005, Loewenstein et al. 2012, Loewenstein et al. 2011, Koch and Schmidt 2010). Still others claim that disclosure laws have limited effects on prescribing behavior (Pham-Kanter et al. 2012, Guo et al. 2017) and, as such, merely increase the cost of doing healthcare. Despite such speculative arguments, however, the interaction of disclosure laws with the mediating channel of industry-physician relationships remain unknown.

It is difficult to analyze the interaction of disclosure law with payments, and no previous study has examined whether payments to physicians from pharmaceutical companies are lower when disclosure is mandatory. Data for this type of comparative empirical analysis are rarely available, have previously been of poor quality (Ross et al. 2007), and data are typically only available for states that have instituted disclosure requirements. Researchers have had to rely on physician self-reporting of payments in non-disclosure states. We bypass this obstacle by utilizing national data released by pharmaceutical companies due to legal settlements unlikely to have been predicted at the time physicians received payments.

The scope and size of our data also make it a more comprehensive industry-wide analysis. Twelve U.S. pharmaceutical companies representing 42% of total pharmaceutical industry rev-

enues released data on payments from 2009-2011 totaling to \$316 million to 316,622 physicians in 50 states and Washington, D.C. States were classified as having disclosure laws that were strong (3 states-Massachusetts, Vermont, and Minnesota), weak (4 states-West Virginia, District of Columbia, Maine, and California), or non-existent (44 states) based on whether data were reported to state authorities (weak) or was made publicly available (strong). Our analysis of state laws is limited by the lack of true randomization of laws or randomization of the assignment of decision-makers responsible for creating the law. There is no way to rule out omitted variables without a randomized control trial of laws, so our study faces the same limitation as other studies of the impact of policies without random assignment. Thus, we use two approaches in our analysis of disclosure laws and payments to physicians. First, we use a multiple regression in a cross-sectional framework and assess whether our estimates change significantly with the inclusion of controls that may be correlated with both the laws and the payments. Our second approach employs a differences-in-differences panel framework to control for unobserved differences that are fixed within states. In both analyses, we find that state-mandated public disclosure of pharmaceutical payments to physicians was associated with lower statewide average payment per physician, but higher payments among the subset of physicians with industry relationships. The quantitative estimates across all payments and for each payment category were similar, which reduces the concern that our results are due to omitted variables, though we cannot completely rule out that possibility.

For one state - Massachusetts - existing state-mandated disclosures first became publicly available during our sample period, allowing separate analyses of the association between disclosure laws and public visibility of disclosed data while the administrative cost of reporting data remained fixed for pharmaceutical companies. We use the date the data became publicly visible as the treatment date for two reasons. First, this allows disentangling the behavioral response by physicians to mandatory disclosure from the behavioral response by industry to the costs of complying with mandatory disclosure. Second, we lack data covering the period before the date the state-mandated disclosure data began to be collected. The results corroborate the cross-sectional finding. While the number of payments to physicians decreases, the average amount of payments increases among physicians who accepted payments. This suggests that the public visibility of the disclosed data, rather than the disclosure itself, is the primary mechanism behind our findings.

This is further corroborated by the fact that in our analysis states with weak disclosure laws are indistinguishable from states with no disclosure laws.

The rest of the paper proceeds as follows. Section 2 presents the theory which provides intuition for the potential effects of mandatory disclosure on the disclosed activity. Section 3 describes the data. Section 4 explains the empirical strategy and threats to the validity of the identification strategy. Section 5 presents the results. Section 6 discusses the findings and concludes.

2. THEORY

This section seeks to understand why disclosure laws may have behavioral effects. Many papers have modeled expert advisors, but models of mandatory disclosure are scarce. The following is a simple theory for the potential impact of disclosure law on physician payments. First, payments to paid physicians is predicted to increase after mandatory disclosure because of the reputational cost to physicians of having their industry-physician relationships be made public. Second, physicians receiving low payments drop out with mandatory disclosure because it is not worth it to the pharmaceutical companies to continue paying these physicians. We illustrate the intuition in a two-type model and a full model with continuous types in the online appendix. The model contributes to a large, primarily informal, mandatory disclosure literature in law.

In brief, suppose each physician can be categorized according to a certain number of ways in which they may increase pharmaceutical sales. For example, some physicians may be more successful at conducting clinical research that advance marketing claims or find additional indications for a particular drug. Other physicians may be more effective at presenting the results of clinical research to colleagues and affecting peer prescribing behaviors. Some physicians may simply be more behaviorally responsive to payments in their prescribing patterns. The pharmaceutical company's objective, for a given physician type, is to maximize their return from payments. Payments for effective physicians will be higher than the payments for less effective physicians.

Now, consider the effect of disclosure. We assume that disclosure law increases the cost of each physician for the pharmaceutical company. Disclosure effectively makes physicians more reluctant to accept payments. The reputational cost of accepting payments is passed onto the

pharmaceutical company, which then must make higher individual payments to achieve the same effect with a particular physician. Then, mandatory disclosure has two effects. First, mandatory disclosure increases payments to the paid physicians, because for a given physician effort, the payment to the physician increases. Second, mandatory disclosure increases the cutoff threshold for physician effectiveness. The pharmaceutical company will choose not to pay physicians who are less effective than this cutoff. So, mandatory disclosure causes low payments to drop out.

3. DATA

We identified payments to physicians between 2009-2011 using public disclosures from 12 pharmaceutical companies. The combined revenue of the companies represented 42% of U.S. market revenue in 2011.¹ Two companies made payment data available voluntarily, and data from the remaining 10 companies became available due to legal action – typically as a result of legal settlements with the U.S. Department of Justice.² These data were collated and provided by a non-profit journalism organization, ProPublica. We conducted several validation checks of the data. First, we validated this database with data obtained directly from seven pharmaceutical companies. ProPublica assembled data on payments to physicians from 12 pharmaceutical companies, between the third quarter of 2009 and fourth quarter of 2011. This compilation was important because historical data are not easily obtainable from all pharmaceutical companies directly. For example, some companies remove data from their website at the end of each quarter or year. We partially validate the quality of the ProPublica data, by comparing it with data obtained directly from Eli Lilly, for payments made to physicians during 2010. We found a match of greater than or equal 97.5% for the number of physicians and total amount of payments, in each category and overall. Similarly high match rates were found for AstraZeneca payments made in 2010, GlaxoSmithKline payments made in 2009 Quarters 2 to 4, Johnson & Johnson payments made in 2010, Merck payments made from 2009 Quarter 3 to 2010 Quarter 4, Valeant payments made in 2010 Quarters 1 to 3, and Viiv payments made in 2010.³ Other data were not reported in a quarterly or yearly time frame available for comparison. When we excluded voluntarily disclosed data in robustness checks of our specifications, the results were similar.

¹Appendix 1, which reports background information on these companies, displays this information in Panel A.

²Appendix 1 Panel B summarizes the conditions for each pharmaceutical company disclosing the payments.

³Appendix 1 Panel C presents a full discussion of the validity of our data.

Our data contained 579,652 payments made from the third quarter of 2009 to second quarter of 2011. We also excluded 707 payments for which an individual recipient could not be identified. 316,622 physicians and \$316 million in payments were represented in our data. Each payment included the name of the pharmaceutical company providing payment, name and city of the physician receiving payment, date, amount, and category of payment (consulting, speaking, research, meals, travel/lodging, items, other, or combination of above categories). We cannot verify whether pharmaceutical companies assigned the most relevant payment category to transactions, as contract terms are typically private and may include provision of promotional or marketing support (Steinbrook 2009).

If a payment range was specified (e.g., “\$10,001-\$20,000”), the average reported payment within that range was used. Most companies reported data at the annual level, so we generated equivalent data for the remaining companies by summing the payments by year. Physician identifiers were created based on the same name (first, last, and middle) and city appearing in multiple disclosure records. For a match across payment records, we required the same first and last name, and either the same middle name (or initial) or city; no other data were available for the match.

Various governmental and non-profit organizations provided data on statewide health and socioeconomic conditions.⁴

We classified state disclosure laws as “strong” if states required payments to physicians to be publicly available, “weak” if states required payments to physicians to be reported to the state but not the general public, and “none” if states did not require reporting of payments to physicians. Table 1 summarizes the dates of passage of laws and categorizes the strength of disclosure laws by state. In Massachusetts, payments from drug companies and medical device makers to healthcare providers were required to be disclosed to the general public. In Minnesota, payments of over \$100 from wholesale drug manufacturers to practitioners were required to be generally disclosed to the public. In Vermont, payments from prescription drug companies to healthcare providers were required to be disclosed to the general public. In Massachusetts, the data became publicly searchable on a website in November 2010. For Minnesota and Vermont, the data can be requested from the state attorney general offices. In West Virginia, payments above \$100 from drug companies to healthcare providers, for the purpose of advertising prescription

⁴These variables are listed along with their sources in Appendix 2.

drugs were disclosed to the state. In Maine and the District of Columbia, payments for seminars, informational programs, trips and travel, food, entertainment, or gifts valued at more than \$25 and anything provided to a healthcare professional for less than market value were required to be disclosed to the state. In California, pharmaceutical companies are required to self-impose an annual limit on marketing expenses to healthcare professionals. In West Virginia, District of Columbia, Maine, and California, any payment data disclosed to the state was kept confidential.

3.1. *Outcomes*

The main dependent variable was the log of average payments per year⁵, calculated as the total annual amount paid to all physicians in a state each year (“statewide payments”) divided by the number of physicians with active licenses in each state (“number of active physicians”). In additional tests, we examined the share of statewide payments in each category and number of physicians accepting any payment. We also analyzed annual payments to individual physicians among the subset of physicians who accepted at least one payment (“paid physicians”) as well as the distribution of payments above and below \$1,000 and \$100 – the limit on industry gifts to physicians suggested by both the AMA (1992) and Pharmaceutical Researchers and Manufacturers of America (2009).

3.2. *Potential Confounders*

The national data released by pharmaceutical companies due to legal settlements was unlikely to have been predicted at the time physicians received payments. However, there may be potential confounders that influence the interest of pharmaceutical companies in associating with physicians in these states. These potential confounders broadly divide into factors associated with supply and demand for payments. Supply factors may stem from pharmaceutical companies interested in physicians in states with a larger elderly population (reflecting a bigger market share for prescription drugs) or with more health insurance, wealth, or education (where patients can afford prescription medications). Dense populations, more physicians with active licenses, or

⁵We used logs because distribution of payments was more reflective of log-normal rather than normal distribution.

nurses with active licenses may make pharmaceutical associations more effective, for example, through more interaction with other physicians on a regular basis, whether casual or through well-attended speaking engagements. Demand for payments derive from physicians who, earning a lower income or residing in states with a higher cost of living, may have greater interest to supplement income through payments from pharmaceutical companies. We obtain cost of living, average physician wages, median household income, and the proportion of individuals with health insurance from the US Departments of Labor and Commerce. We measure population density and the proportion of individuals under 18 years of age (who may demand different medications), greater than or equal to 65 years, and with at least a high school education from the U.S. Census Bureau. The Kaiser Family Foundation provided data on the average number of retail prescriptions per person that were filled at pharmacies in 2011. The AMA and American Hospital Association provided data on the number of physicians and nurses in each state with active licenses, respectively.

In robustness checks, we used sparse models to assist in the selection of controls (Belloni et al., 2014, Belloni et al. 2012). Controlling for a large set of variables is desirable from the standpoint of mitigating potential biases underlying the interpretation of the disclosure law coefficient. The downside is that controlling for too many variables may make estimates become less precise. The researchers are faced with a trade-off between the precision of the estimate and the plausibility of the conditional exogeneity assumption. By including additional controls in the specification, we make the conditional exogeneity assumption more plausible. At the same time, the precision of estimates is potentially reduced. The double selection method by LASSO offers a rigorous approach to achieving a balance between exogeneity and precision (Belloni et al., 2014, Belloni et al. 2012).⁶

Formally, LASSO modifies ordinary least squares by minimizing the sum of squared errors subject to the sum of the absolute value of all coefficients being less than a constant. This constraint tends to set some coefficients to exactly 0, reducing model complexity by identifying only the most important variables. Estimation proceeded in two steps. First, LASSO selected the control variables that predict the strength of the disclosure law. This step helps to ensure robustness by

⁶The tables in Appendices 3 and 7 reports the results using LASSO to select potential confounders, and the result of this selection is reported in Appendix 8.

finding control variables that are strongly related to the treatment and thus potentially important confounds. Next, LASSO selected control variables that were predictive of payments. This step helps to ensure that important elements are included in the equation, helping keep the residual variance small as well as intuitively providing an additional chance to find important confounds. LASSO used a set of potential confounding factors constructed from the original controls and, as standard practice, all two-way interactions between any two controls.⁷ The original controls plus LASSO-selected control variables were then included as independent variables.⁸ LASSO is not a perfect solution to omitted-variables bias: the cross-sectional regressions can still be misleading to the extent that important confounding factors are left out of the feature set, hence the need for a difference-in-difference approach to complement the cross-sectional approach.

4. ESTIMATION FRAMEWORK

4.1. *Cross-sectional specification*

Our multiple regression model used the following framework:

$$(1) \quad \log(Y_{st}) = \beta_0 + \beta_1 Law_{st} + \beta_2 Year_t + \beta_3 X_{st} + \epsilon_{st},$$

where Y_{st} is the ratio of sum of all payments received, over the number of active physicians in state s , year t .⁹ Law_{st} are dummy variables indicating strength of disclosure laws in state s , year t (strong, weak, or none (the omitted category)); $Year_t$ is a dummy for each year in our sample; and X_{st} are state and year controls, including the share of payments from each company, the share of payments for each category of payment, and health and socioeconomic controls as described above. We use heteroscedasticity-robust Huber-White standard errors or standard errors clustered at the state level.

⁷Additional description of and motivation for the LASSO variables are in Cohen and Chen (2010).

⁸We also included Share of Payments from Each Pharmaceutical Company by Value and by Count and Share of Payments in each Payment Category by Value and by Count. However, all results at the state and physician level and at various thresholds were robust to dropping control variables for share of payments from each company and share of payments for each category of payment. In fact, the relationships became larger and more statistically significant.

⁹We specified payments in logs because we rejected the hypothesis that payments in non-log terms were normally distributed using the one-sample Kolmogorov-Smirnov test against the theoretical distribution.

For alternative specifications, we also looked at:

$$(2) \quad \log(Y_{ist}) = \beta_0 + \beta_1 Law_{st} + \beta_2 Year_t + \beta_3 X_{st} + \epsilon_{ist}$$

where Y_{ist} is now sum of all payments received by physician i in state s , year t , and the right-hand side variables having the same notation as the aggregate version. When we analyze payments above or below cutoffs like \$1,000 and \$100, we check robustness of the results to implementing truncated regressions.¹⁰

Finally, for the third specification, we looked at:

$$(3) \quad \log(Y_{cst}) = \beta_0 + \beta_1 Law_{st} + \beta_2 Year_t + \beta_3 X_{st} + \epsilon_{cst},$$

where now Y_{cst} is the sum of category c payments received, divided by the sum of all payments in state s , and year t .

4.2. Differences-in-differences specification

Massachusetts offers a special setting to study what happens after public visibility of disclosed data while the administrative cost of reporting data remains fixed for pharmaceutical companies. This is possible because existing state-mandated disclosures first became publicly available during our sample period. Analyzing public visibility in a differences-in-differences framework helps discriminate between physician response to mandatory disclosure from the industry response to the costs of compliance.

For the differences-in-differences specification, we used the following framework:

$$(4) \quad \log(Y_{st}) = \beta_0 + \beta_1 \mathbb{1}_M + \beta_2 \mathbb{1}_M Post_t + \beta_3 Year_t + \beta_4 X_{st} + \epsilon_{st},$$

¹⁰To reduce the impact of outliers, we also replaced the top 0.5% of payments with the 99.5th percentile. We varied this parameter between the top 0.5% and 2.5%, with similar results. Results were robust to eliminating payments reported in ranges.

where Y_{st} is the sum of all payments, over the number of active physicians in state s , year t ; $\mathbb{1}_M$ is an indicator variable for the state of Massachusetts; $Year_t$ and X_{st} are as defined before; the year fixed effects absorb the post dummy. Standard errors are clustered at the state level.

As an alternative specification, we also consider:

$$(5) \quad \log(Y_{ist}) = \beta_0 + \beta_1 \mathbb{1}_M + \beta_2 \mathbb{1}_M Post_t + \beta_3 Year_t + \beta_4 X_{st} + \epsilon_{ist},$$

where Y_{ist} is now sum of all payments received by physician i in state s , year t , and the right-hand side variables having the same notation as the aggregate version.

To assess the validity of our estimates, we used randomization inference: we re-ran these regressions, re-assigning the indicator variable to another state. We report whether the true β_2 falls outside the 90 or 95% range of placebo β_2 estimates. There is no pre-trend data to assess parallel pre-trends before the data were revealed online because most of the data is yearly. In the appendix, we employ synthetic control and report point estimates similar to the main estimates.

5. RESULTS

5.1. *Cross-sectional association between disclosure laws and payments (state-level analysis)*

We preview our results with mean statistics and distributional visualizations before moving to the regression analyses. First, we looked at differences in payments between states with strong, weak, and no disclosure laws. We compared the magnitude and category of payments according to disclosure status. Table 2 presents summary statistics. In the bottom of the first panel, 11% of physicians in strong-disclosure states accepted payments, versus 37% and 42% of physicians in states with weak and no disclosure laws, respectively. Among the 316,622 physicians¹¹ who accepted payments across the U.S., the average annual payment was \$1,377 (standard deviation=\$6,694).¹² The second panel displays the average payments per physician in the different states. It shows that statewide payments per physicians is \$221 in strong-disclosure states and \$334 in weak-disclosure states and \$411 in non-disclosure states. Speaking fees comprise the

¹¹316,622 = 6,689 + 38,209 + 271,724 from the third row of this panel.

¹²This is the weighted average of the final row of the third panel.

largest share across all categories and states. It also shows that strong-disclosure states have lower average payments for speaking and for meals and higher payments for consulting. The third panel displays the average payments per paid physician in the different states. It shows that physicians in strong-disclosure states had proportionately larger payments for consulting. The absolute payment amount for research activities is larger in strong-disclosure states. The fourth panel displays the proportional distribution of payments across payment types for different categories of disclosure law strength. It shows similar patterns are also present in terms of proportions.

Figure 1A displays the density of payments by strength of disclosure law. It displays annual payments among paid physicians (observations are at the physician-year level). The density line for states with no disclosure law and for states with weak disclosure law indicates that in both groups of states, 90% of the annual payments among paid physicians are below \$1000 (this can be seen clearly from the cumulative density plot in the online appendix). In strong disclosure states (Massachusetts, Minnesota, and Vermont), 81% of the physicians were paid less than \$1000 annually. Figure 1A also displays the strong disclosure states separately. Massachusetts – the state with the most recent implementation of a strong disclosure law – exhibited the lowest proportion of paid physicians receiving payments greater than \$1,000 among strong-disclosure states and diverged least from weak and non-disclosure states in this regard. States under strong disclosure laws for longer periods of time had higher proportions of highly paid physicians. The distributions were significantly different at $P=0.001$.

Figures 1A and 1B present a separate study of the \$100 cut-off. The disclosure obligations in one strong disclosure state (Minnesota) and one weak disclosure state (West Virginia) required payments of over \$100 to be reported to the public or state attorney general offices. However, litigation settlements obliged all payments to be reported. Figure 1A shows that up to 60% of annual physician payments are less than \$100 in Minnesota (this can be seen clearly from the cumulative density plot in the online appendix), which is in between the percentage share for the other two strong disclosure states (Massachusetts and Vermont), which is suggestive evidence that administrative burden of reporting was not a significant determinant of the payments. In other words, to the extent the administrative burdens surrounding payments in excess of \$100 and lack of administrative burdens for payments under \$100 meant that payments under \$100

should be more common (than in states without disclosure obligations), this is not apparent from comparing Minnesota with Massachusetts (which has a greater share of payments under \$100). Figure 1B presents another interesting feature of the data at the discontinuity (since Figure 1A uses an Epanechnikov kernel to smooth the data, Figure 1B presents only the data for values from \$98 to \$102). There is a discontinuity in payments for Minnesota at \$100, with 18 payments of \$99 and 3 payments of \$100. In contrast, for non-disclosure states, the number of payments varies smoothly around \$100, with 2,806 payments of \$99 and 2,260 payments of \$100. Moreover, the distribution for West Virginia is similar to the distribution of payments for no disclosure states, with 23 payments of \$99 and 16 payments of \$100. This difference-in-discontinuity supports the view that disclosure affects the reputational costs to physicians, who would discontinuously experience this cost at \$100 and only in strong disclosure states.

Next, Table 3 presents multiple regression models to relate physician payments to the presence of strong, weak, or no disclosure laws, controlling for the pharmaceutical company providing payment, category of payment, year, and controls described above. The unit of analysis is the state-year with 153 observations across 3 years. Adjusted for all controls, statewide payments per physician were 49% lower in strong-disclosure states (95% CI=-0.716,-0.259, $P<0.001$, Table 3) than in non-disclosure states. Statewide payments were not significantly lower in weak-disclosure states (coefficient=-0.176, 95% CI=-0.394,0.041, $P=0.11$) (Table 3) than in non-disclosure states. Both of these results are consistent with regression models that include different sets of potential confounds.¹³

Using multiple regression models, we also estimated the relationship between disclosure laws and the share of payments in each category, and the relationship between disclosure laws and the number of physicians receiving payments. Compared to total payments per category in non-disclosure states, adjusted for all controls, the share of total payments per category in strong-disclosure states was as follows: 10.5% lower share for speaking ($P=0.005$), 3.1% lower share for meals ($P=0.05$), and 9.4% higher share for consulting ($P<0.001$)¹⁴. Weak-disclosure states had, in contrast, a 2.8% higher share of payments for meals and 2.1% lower share of payments for consulting than in non-disclosure states (both $P=0.05$). A chi-squared test of differences between

¹³Appendix 3 displays a sequence of models where control variables are gradually added to assess sensitivity of the main results.

¹⁴Appendix 4 reports the complete set of regression coefficients.

payment categories by strength of disclosure laws was significant ($P < 0.001$).

5.2. *Cross-sectional association between disclosure laws and payments (physician-level analysis)*

Next, we analyzed the association between disclosure laws and payments received by physicians at the individual (rather than state) level. The unit of analysis is physician-year. Table 3, column 2 considers the subset of physicians who accepted any payment from pharmaceutical companies. In strong-disclosure states, annual payments among physicians who accepted any payment were 10.1% higher (95% CI=0.0096-0.193, $P=0.03$) than in non-disclosure states. This result is robust to various sets of controls.¹⁵ Average annual payments among physicians who accepted any payments was \$2,436 in strong-disclosure states and \$1,340 in non-disclosure state (and \$1,467 in weak-disclosure states). In weak-disclosure states, annual payments were 8.8% lower ($P < 0.001$) than in non-disclosure states, but the sign of this association was reversed in specifications with fewer controls.

We evaluated different thresholds for payments to ascertain the parts of the payment distribution that were associated with disclosure laws. Doing so assesses a prediction of the model. The model says that (1) low-money physicians simply drop out and (2) high-money physicians get more money. We used a multiple regression analysis similar to the aggregate approach. The unit of analysis is physician-year. Some specifications include only physician-years when a physician received any payments. Other specifications include all active physician-years, assigning \$0 to physicians not receiving payments.

In strong-disclosure states, annual payments among physicians who accepted greater than \$100/year were 54% higher (95% CI=0.411-0.675, $P < 0.001$) (Table 3, column 3) than in non-disclosure states. No statistically significant association was observed between strong disclosure laws and the number of physicians who accepted greater than \$100/year. However, in strong-disclosure states, roughly 19% of paid physicians accepted payments greater than \$1,000, compared with only 10% of physicians in weak-disclosure states and non-disclosure states. States with less time spent under strong disclosure laws had a smaller percentage of paid physicians accepting payments greater than \$1,000.

¹⁵Appendix 3 sequentially adds controls in models 7-9.

No statistically significant association was observed for strong disclosure laws and size of payments among paid physicians who accepted less than or equal to \$100/year, but the number of such physicians was 68% lower (95% CI=0.058-1.294, P=0.032)¹⁶ than in non-disclosure states. When including all physicians (not just those who received payments), annual payments among physicians who accepted less than or equal to \$100/year were 25% lower (95% CI=0.249-0.260, P<0.001) (Table 3, column 4). Payments among physicians who accepted less than or equal to \$100/year were significantly different in states with weak versus no disclosure laws, but the significance disappears in the truncated regression with clustering at the state level.¹⁷

5.3. *Differences-in-differences association between disclosure laws and payments*

One state in our sample, Massachusetts, enacted a strong disclosure law in January 2009, but first publicly released data in November 2010 (Kowalczyk 2010). To examine the impact of this release, we ran a differences-in-differences analysis that compared the change in payments in Massachusetts pre- versus post-November 2010 with the change in payments in all other states (none of which altered transparency during this time period). Units of analysis are state-year and physician-year.

Following public release of disclosed payments, payments per physician in Massachusetts decreased 36% (P<0.001) (Table 3, column 5) relative to all other states (which did not change publication of disclosures during this time period). The share of Massachusetts payments declined by 7% for speaking and 4% for meals, but rose 9% for research and 1% for consulting (the first three P<0.001 and the last P<0.1).¹⁸ However, because of the large decrease in payments per physician overall, the absolute amount within each of the categories was reduced. When we used randomization inference, re-assigning the indicator variable to each of the other states, the estimated decrease for overall payments, meals, travel, was between the 90th and 95th percentile of the alternative estimates.

Although not statistically significant, the number of Massachusetts physicians receiving any

¹⁶Appendix 5, which reports additional analyses of the relationship between disclosure laws and distribution of payments to physicians, shows this result in column 2.

¹⁷Appendix 7, which reports additional analyses of the relationship between disclosure laws and payments to physicians, shows this result in column 4.

¹⁸The regression analyses of Massachusetts' disclosure is shown in Appendix 6.

payment and payments less than \$100 declined 34% ($P=0.112$) and 13% ($P=0.125$), respectively. Payments among Massachusetts physicians who accepted greater than \$100/year increased 69% ($P<0.001$) while payments among those who accepted less than \$100/year decreased by 6.9% ($P<0.001$) (Table 3, columns 6-7) relative to all other states. When we re-assigned the indicator variable to each of the other states, the estimated decrease in payments among those who accepted less than \$100/year was between the 90th and 95th percentile of the alternative estimates.

6. DISCUSSION AND CONCLUSION

Many hope that disclosure policies will result in more evidence-based prescribing decisions, better patient outcomes, and decreases in total expenditures on prescription drugs – the fastest growing component of healthcare costs. However, the interaction of disclosure laws on the mediating channel of industry-physician relationships remains unknown. The appendix presents a model of the potential impact of disclosure law on the disclosed activity. These effects have not been previously modeled as far as we are aware nor have they been empirically examined. The interaction of disclosure laws on the targeted behavior is typically unknowable since data on disclosed activity rarely exist in the absence of disclosure. We bypass this obstacle by utilizing national data released by pharmaceutical companies due to legal settlements unlikely to have been predicted at the time physicians received payments.

Our first main result is that strong disclosure laws were associated with a 49% lower statewide annual average of payments to physicians and 74% lower proportion of physicians receiving payments. These decreases might be considered an intended result of disclosure legislation. However, among physicians who accepted any payment, annual payments were 10% higher in strong-disclosure states, and payments were 54% higher among physicians who accepted more than \$100/yr.

Physicians in strong-disclosure states had proportionately smaller payments for speaking and for meals and larger payments for consulting. The absolute payment amount for research activities is larger in strong-disclosure states. These observations suggest that rather than stigmatizing industry-physician research relationships, public disclosure of payments may instead encourage explicit and formal delineation of industry-physician relationships around consulting, research

and development activities.

Our second main result is that little association was observed between payments to physicians and disclosure laws that did not mandate disclosure of payments to the public. This finding may explain the limited effects of disclosure laws in West Virginia and Maine on prescribing behavior in two drug classes observed in a recent study (Pham-Kanter et al. 2012). The disclosure requirements in the Affordable Care Act, however, are more similar to the strong disclosure laws in our study.

Our results shed light on whether the interaction of disclosure law with the targeted behavior is mediated through administrative costs imposed on industry or through physicians' willingness to accept payments (our model highlights the reputational cost to physicians of having their industry-physician relationships made public). Two considerations suggest that administrative costs imposed on industry are the lesser of the two mechanisms in our results. First, strong and weak disclosure imposes similar administrative costs. Second, the changes observed in Massachusetts after public release of disclosures were similar to the smaller payments noted for strong disclosure states. In addition, the categories of payments shifted in the same way—more in consulting and research and less in speaking and meals in strong disclosure states—using both cross-sectional and longitudinal variation. These results suggest that the reduction of incidental payments was due to decreased willingness among physicians to accept payments and that the cost of compliance with disclosure requirements did not significantly reduce industry willingness to maintain payment relationships with physicians. Moreover, to the extent that weak disclosure laws can theoretically have other behavioral effects, such as expressive or moral effects that can be reflected in payments, we do not observe them in the data.

Our third main result is that higher payments for paid physicians were observed when physician payments were publicly visible. This result is consistent with physician-level factors such as compensation demanded for increased public visibility and associated reputational costs (Sigworth et al. 2001) or a “compensation race” driven by physicians demanding more for their contracts, the availability of information on colleagues' compensation, and being under-paid (Preker 2007) or a sense of entitlement (Lichter 2008). The observed changes may be due to a compositional shift in the physicians receiving payments or a change in payments within physicians. When we include physician fixed effects, which utilizes doctors' pre-period payment receipts, strong disclo-

sure was associated with higher payments per physician, but the association was not statistically significant at conventional levels. Therefore, some of the differences may be due to composition effects or treatment effects. It is possible that in some instances, physicians who previously received large payments now receive larger payments, and that in other instances, new physicians began receiving the larger payments.

Potential limitations are that we only had data from 12 pharmaceutical companies and to some extent, the analysis relies on the assumption that the variation in laws is uncorrelated with variation in sampling; however, the 12 companies included 7 of the 10 largest firms in the U.S. market, making their activities relevant even if not representative of smaller pharmaceutical firms.¹⁹ Lower payments per physician in strong disclosure states were observed for each of the 12 companies regardless of its size. This alleviates the concern that sampling factors are associated with the identifying variation if the same pattern holds for each company. We also compared the distribution of payments by companies in the ProPublica database and by companies not in the ProPublica database using data from Massachusetts – A Wilcoxon-Mann-Whitney test for significant differences in distributions indicates that the two distributions are not significantly different ($P=0.20$).

Despite potential confounders that limit the ability to make causal statements, our results were similar using both cross-sectional and longitudinal variation. We examined the experience of Massachusetts before and after the state publicly released data on pharmaceutical company payments to physicians. We employed advanced statistical techniques for strengthening cross-sectional studies by using LASSO, a sparse model, to select control variables predictive of the strength of disclosure law and control variables predictive of payments. Results were similar in both the figures displaying the raw data and multiple regressions that included controls.

Finally, although we conducted our regression analysis for differences between small and large amounts at \$100, other cutoffs besides \$100 do not change the findings. In strong disclosure states, there are fewer small payments even at other cut-offs. We also did not observe payments under \$100 to be more common in states with administrative burdens to disclose payments in excess of \$100 (Minnesota) compared to disclosure states without the \$100 cutoff (Massachusetts),

¹⁹Analysis of the entire pharmaceutical company industry is the subject of ERC-funded work by one of the authors using data from the ACA-mandated industry-wide disclosure.

further suggestive that administrative burden of reporting was not a significant determinant of the payments. Notably, comparing two states with the same \$100 disclosure requirement cut-off, the drop-off in payments after \$99 is sharp for the strong disclosure state (Minnesota) but not the weak disclosure state (West Virginia). The difference-in-discontinuity also supports the view that disclosure affects the reputational costs to physicians, who would discontinuously experience this cost at \$100 and only in strong disclosure states.

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Table 1. States Mandating Disclosure of Pharmaceutical Company Payments to Physicians

State	Effective Date	Information Disclosed	Restrictions on Access	Source
Disclosure Laws With Public Reporting (“Strong”)				
Massachusetts	Jul 2009	Payments from drug companies and medical device makers to health care providers	None, but first publicly released in Nov 2010	1
Minnesota	Jan 1997	Payments of >\$100 from wholesale drug manufacturers to practitioners	Generally public, but some information is subject to trade secret and other restrictions	2
Vermont	Jun 2002	Payments from prescription drug companies to health care providers	None	3
Disclosure Laws Without Public Reporting (“Weak”)				
West Virginia	Apr 2009	Payments of \$100 from drug companies to health care providers, for the purpose of advertising prescription drugs	Confidential	4
District of Columbia	Jul 2004	Payments for seminars, informational programs, trips and travel; food, entertainment, or gifts valued at >\$25; anything provided to a health care professional for less than market value.	Confidential, except for aggregate data	5
Maine	Jan 2006	Payments for seminars, informational programs, trips and travel; food, entertainment, or gifts valued at >\$25; anything provided to a health care professional for less than market value.	Confidential, except for aggregate data	6
California	Jan 2005	Pharmaceutical companies must self-impose an annual limit on marketing expenses to health care professionals	No disclosure requirement	7
No Disclosure Laws*				
Ohio	Proposed bill	Proposed bill would require pharmaceutical manufacturers to submit annual reports listing gifts to physicians who are authorized to prescribe drugs	Not specified	8
Federal (U.S.)	Mar 13	All payments and transfers of value. Pre-empts state laws that are similar or weaker than this provision.	None	9

*Analyzed as part of No Disclosure group, but noteworthy

¹ Commonwealth of Massachusetts. Part I: Administration of the Government Title XVI Public Health. Chapter 111N: Pharmaceutical and Medical Device Manufacturer Conduct. Section 6: Disclosure of Data Relating to Provision of Economic Benefits Valuing Fifty Dollars or Greater.

² Minnesota Statutes 151.461, 2006.

³ 18 V.S.A. “ 4631a-4632. Expenditures by Manufacturers of Prescribed Products-Disclosure of Allowable Expenditures and Gifts by Manufacturers of Prescribed Products. Title 18: Health. Chapter 91: Prescription Drug Cost Containment. Vermont Statutes Online.

⁴ West Virginia Code St. R. § 206-1-3. Required Disclosure.

⁵ District of Columbia General Code Sections 48-833.01 to 48-833.09.

⁶ Title 22: HEALTH AND WELFARE. Subtitle 2: HEALTH. Part 5: FOODS AND DRUGS. Chapter 603: PRESCRIPTION DRUG ACCESS HEADING: PL 1999, C. 786, PT. A, §3 (NEW). Subchapter 4: PRESCRIPTION DRUG PRACTICES HEADING: PL 2003, C. 456, §1 (NEW). §2699. Prescription drug practices (REPEALED).

⁷ California Health and Safety Code. Section 119400-119402.

⁸ Ohio Senate, Senate Bill 79.

⁹ 42 USC 1320a-7h.

Table 2. Summary Statistics for Pharmaceutical Company Payments to Physicians, by Strength of Disclosure Laws, 2009-2011.

Variable	Category	Strength of Disclosure Laws		
		With Public Reporting ("Strong")	Without Public Reporting ("Weak")	None
N States		3	4	44
N Active Physicians*		43,820	109,041	646,630
N Paid Physicians		6,689	38,209	271,724
N Payments		11,039	69,759	498,147
Number of Physicians Accepting Any Payment / Number of Active Physicians (%)**		10.73	36.56	42.31
Average Annual Statewide Payments / Number of Active Physicians				
\$	Consulting	33.52	15.92	18.91
	Speaking	130.34	233.09	255.71
	Research	30.91	35.30	68.49
	Other Categories	26.08	50.09	68.34
	Total	220.85	334.40	411.45
Average Annual Payments / Physician, Among Physicians Who Accepted Any Payment				
\$	Consulting	1046.49	314.79	282.96
	Speaking	3692.35	2909.10	2855.72
	Research	1030.37	150.26	207.20
	Other Categories	354.05	466.93	470.89
	Total	2436.35	1466.84	1340.24
Share of Statewide Payments				
%	Consulting	15.38	5.79	5.05
	Speaking	53.59	64.28	61.74
	Research	22.23	13.94	18.92
	Other Categories	8.80	15.99	14.29
Year	2009	7.32	3.49	3.59
	2010	64.33	60.95	61.65
	2011	28.35	35.56	34.75
Statewide Variables				
Real Income Per Capita (\$)*		29,781	29,095	26,782
Average Physician Wage (\$)		194,797	190,758	188,748
Cost of Living Index		115.32	121.33	102.86
Population < 18 y (%)		21.99	21.59	24.25
Population ≥ 65 y (%)		13.59	13.58	13.05
≥ High School Education (%)		90.84	85.24	87.12
Health Insurance (%)		76.96	68.28	71.11
Number of Retail Prescriptions Filled at Pharmacies (Person/Year)		12.23	13.15	12.14
Population Density (Thousands/Square Mile)		249.10	2298.41	162.06
Number of Physicians with Active Licenses		14,607	27,260	14,696
Number of Nurses with Active Licenses		43,933	67,815	45,775

*Data for 2010.

**Average per state.

Table 3. Relationship Between Disclosure Laws and Payments to Physicians, 2009-2011. [±]

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unit of Analysis	State-Year	Physician-Year	Physician-Year	Physician-Year	{ Difference in Payments Between MA and All Other States, Before and After Public Release of MA Payments } [‡]		
Dependent Variable	Log Annual Payments Per Active Physician	Log Annual Payments Among Paid Physicians	Log Annual Payments Among Physicians Who Accepted >\$100	Log Annual Payments Among Physicians Who Accepted ≤\$100 [‡]	Log Annual Payments Per Active Physician	Log Annual Payments Among Physicians Who Accepted >\$100	Log Annual Payments Among Physicians Who Accepted ≤\$100 [‡]
Independent Variable							
Disclosure Laws With Public Reporting (“Strong”)	-0.488***	0.101*	0.543***	-0.254***			
P	<0.001	0.0304	<0.001	<0.001			
(95% CI)	(-0.716, -0.259)	(0.0096, 0.193)	(0.411, 0.675)	(-0.260, -0.249)			
Disclosure Laws Without Public Reporting (“Weak”)	-0.176	-0.0880***	0.036	-0.0613***			
P	0.111	<0.001	0.34	<0.001			
(95% CI)	(-0.394, 0.041)	(-0.130, -0.0458)	(-0.039, 0.111)	(-0.0767, -0.0458)			
Massachusetts x After Public Release in MA					-0.356***	0.691***	-0.0686***
P					<0.001	<0.001	<0.001
(95% CI)					(-0.465, -0.247)	(0.605, 0.778)	(-0.0846, -0.0527)
N	153	425,797	139,019	2,257,059	153	141,736	2,257,059
R ²	0.99	0.215	0.172	0.099	0.972	0.170	0.098

[±]Adjusted for company providing payment, category of payment, year, and statewide demographics. Demographics are household income, average physician wage, cost of living, % population < 18, % population ≥ 65, % unemployment, % ≥ high school education, % health insurance, annual prescription drugs filled at pharmacies/person, population density, number of active physicians, and number of active nurses. Full results displayed in Appendix 3. Additional LASSO controls in Appendix 8. Robust standard errors.

[‡]Included a zero for physicians who accepted no payments.

[‡]Standard errors clustered at the state-level.

Figure 1. Density of Payments To Physicians Who Accepted Payments (\$), 2009-2011.

Figure 1A

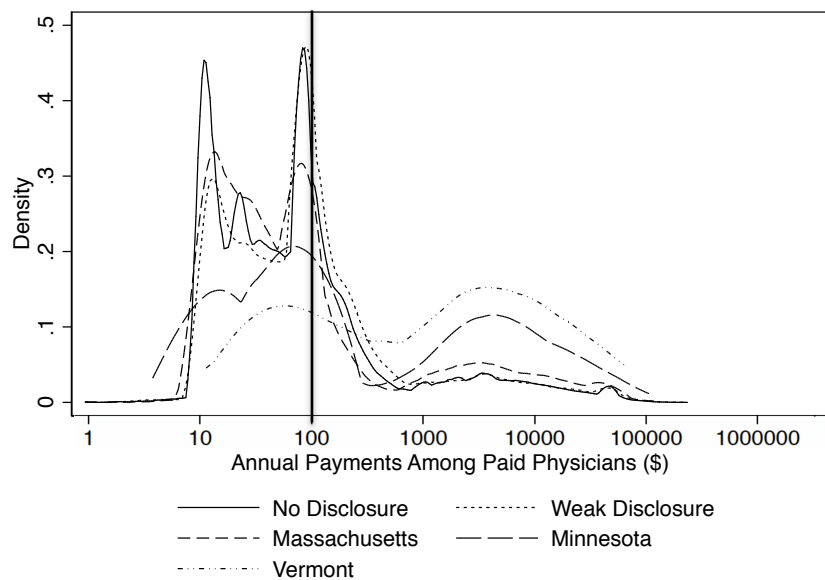
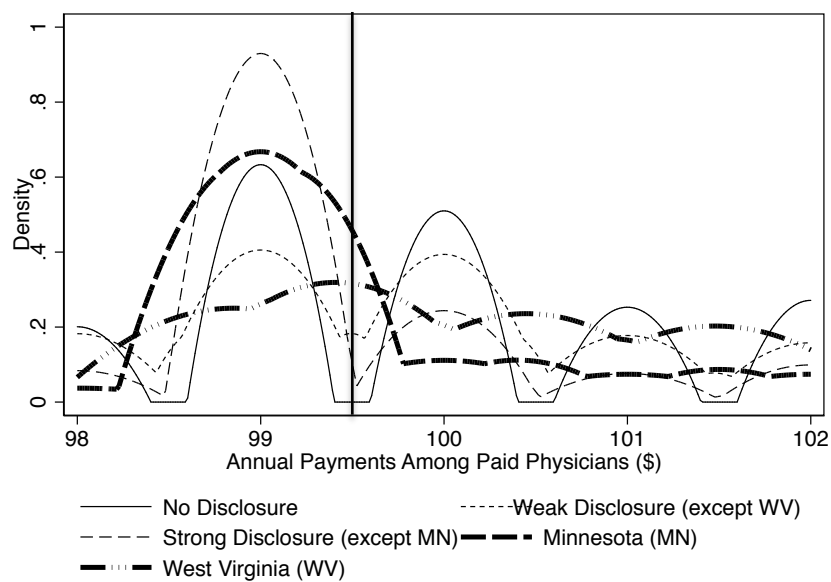


Figure 1B



REVIEWER SUPPLEMENT

Appendix 1. Disclosure of Pharmaceutical Company Payments to Physicians

Panel A: Size of Database, May 2012

Company	Revenue (\$ Billion, 2011)	Market Capitalization (\$ Billion, May 2, 2012)
Allergan	5.42	29.37
AstraZeneca	33.59	56.25
Cephalon*	18.31	43.08
Eli Lilly	24.29	47.86
EMD Serono**	N/A	N/A
GlaxoSmithKline	43.93	117.82
Johnson & Johnson	65.03	179.03
Merck	48.05	119.79
Novartis	58.57	151.26
Pfizer	67.43	171.7
Valeant	2.46	16.79
ViiV**	N/A	N/A
Total of Companies in Data	367.08	932.95
Size of Pharmaceutical Market	869.85	2,090.00
Market Share	42.2%	44.6%

*Data shown for Teva, which acquired Cephalon in 2011.

*Private company; data not available.

**Owned by GlaxoSmithKline and Pfizer.

Sources:

Global Industry Classification Standard. Health Care-Pharmaceuticals-Pharmaceuticals. New York, NY: MSCI and Standard and Poor's, 1999. Accessed at <http://www.msci.com/products/indices/sector/gics/>, May 2, 2012.
Bloomberg LP, Accessed at www.bloomberg.com, May 2, 2012.

Panel B: Categories of Payments Reported by Companies Currently Disclosing Payments to Physicians (Source¹⁻¹²)

Our data contained 579,652 payments made from the third quarter of 2009 to second quarter of 2011. Their data sources are listed below:

Company	Payments Disclosed	Disclosure Reason	Disclosure Effective Date	Disclosure Expiration Date
Allergan	Phase I: Payments for speaking, meals, and advisory boards of the Sales, Marketing, and Medical Affairs divisions. Phase II: All payments and transfers of value.	Legal settlement for alleged off-label marketing and illegal payments to physicians to induce prescriptions.	Phase I: 9/1/10 Phase II: 9/1/11	8/30/15
AstraZeneca	Phase I: Speaker fees. Phase II: Payments for consulting, speaking, meals, travel, research, certain educational items, royalties and license fees, and ownership and investment interests, when made directly or indirectly by AstraZeneca's US business.	Legal settlement for alleged off-label marketing and illegal payments to physicians to induce prescriptions.	Phase I: 8/31/10 Phase II: 8/31/11	4/27/15
Cephalon (Acquired by Teva-2011)	Phase I: Payments for speaking, meals, and advisory boards of the Sales, Marketing, and Medical Affairs divisions. Phase II: All payments and transfers of value.	Legal settlement for alleged off-label marketing.	Phase I: 1/31/10 Phase II: 3/31/11	9/26/13
Eli Lilly	Phase I: Payments for speaking, meals, and advisory boards of the Sales, Marketing, and Medical Affairs divisions. Phase II: All payments and transfers of value.	Guilty plea in criminal lawsuit and settlement in civil lawsuit for alleged off-label marketing.	Phase I: 8/1/09 Phase II: 8/1/10	1/14/14
EMD Serono	All payments and transfers of value	Legal settlement for alleged illegal payments to physicians to induce prescriptions.	7/1/11	4/20/15
GlaxoSmith Kline	Phase I: Payments for consulting and speaking. Phase II: Added payments for clinical research to lead investigators.	Voluntary	Phase I: 4/1/09. Phase II: 1/1/10.	None
Johnson & Johnson	All payments and transfers of value from Johnson & Johnson's US businesses	Voluntary	6/30/10	None

Merck	Phase I: Payments for speaking. Phase II: All payments and transfers of value.	Phase I: Voluntary. Phase II: Legal settlement for alleged off-label marketing.	Phase I: 11/22/16 9/1/09. Phase II: 6/1/12
Novartis	Phase I: Payments for speaking. Phase II: All payments and transfers of value, except for research, development, and clinical investigations. Phase III: All payments and transfers of value.	Legal settlement for alleged illegal marketing and remuneration to physicians to induce prescriptions.	Phase I: 9/29/15 3/31/11 Phase II: 3/1/12 Phase III: 3/1/13
Pfizer	All payments and transfers of value	Guilty plea for misbranding Bextra and legal settlement for alleged illegal payments to physicians to induce prescriptions.	3/31/10 8/31/14
Valeant	All payments and transfers of value	Guilt plea to violation of U.S. Anti-Kickback Statute and legal settlement for alleged illegal payments to physicians to induce prescriptions.	4/30/10 9/11/14
ViiV	Speaking and consulting fees to lead investigators. Includes payments from Pfizer and GlaxoSmithKline, which own ViiV.	Part of Pfizer settlement (above)	1/1/10 8/31/14

¹ Settlement Agreement Between United States and Allergan, United States ex rel. Amy M. Lang and Charles J. Rushin v. Allergan, Inc., Civ. No. 1:07-cv-1288-WSD (N.D. Ga., 2010), available at <http://www.taf.org/botox-final-settlement-2010.pdf>. Original document available with authors.

² Settlement Agreement Between United States and AstraZeneca, Inc., United States of America ex rel. James Wetta v. AstraZeneca Corporation, Civ. No. 04-3479, available at http://www.justice.gov/usao/pae/Pharma-Device/astrazeneca_settlementagreement.pdf. Original document available with authors.

³ Biopharmaceutical Company, Cephalon, to Pay \$425 Million & Enter Plea to Resolve Allegations of Off-Label Marketing, available at <http://www.justice.gov/opa/pr/2008/September/08-civ-860.html>. Original document available with authors.

⁴ Settlement Agreement Between United States and Eli Lilly, United States of America ex rel. Robert Rudolph, et al., v. Eli Lilly and Company, Civ. No. 03-943, available at <http://www.justice.gov/usao/pae/News/2009/jan/lillysignedsettlementagreement.pdf>. Original document available with authors.

⁵ Settlement Agreement Between United States and Serono Laboratories, United States ex rel. Timothy Amato v. Serono Laboratories, et. al., Ca. No. RDB-05-3457, available at <http://freepdfhosting.com/c1dacbb785.pdf>. Original document available with authors.

⁶ GSK, Commitment to Transparency and Access, available at <http://us.gsk.com/html/responsibility/transparency-access.html>. Original document available with authors.

⁷ Johnson & Johnson Transparency in Our Business Activities, available at <http://www.jnj.com/connect/about-jnj/our-citizenship/transparency-in-our-business-activities>. Original document available with authors.

⁸ Settlement Agreement Between United States and Merck & Co., Inc., United States of America v. Merck Sharp & Dohme Corp., Crim. No. TBA, available at <http://www.justice.gov/usao/ma/news/2011/November/2011114024353852.pdf>. Original document available with authors.

⁹ Settlement Agreement Between United States and Novartis, United States et al. ex rel. Austin and Montgomery v. Novartis Pharmaceuticals Corp., Civ. No. 8:03-cv-1551-T-30-TGW, available at http://www.justice.gov/usao/pae/News/2010/Sept/novartis_settleagreement.pdf. Original document available with authors.

¹⁰ Settlement Agreement Between United States and Pfizer, United States et al. ex rel. Blair Collins v. Pfizer, Inc., Civ. No. 04-11780-DPW. Original document available with authors.

¹¹ Valeant Pharmaceuticals Int'l., Quarterly Report Pursuant to Section 13 or 15(d) of the Securities and Exchange Act of 1934 (Form 10-Q) (Sept. 30, 2010). Original document available with authors.

¹² ViiV Healthcare, Payment to US Healthcare Professionals for Research and Development Activity, available at http://www.viivhealthcare.com/about-us/corporate-ethics/payments-to-healthcare-professionals.aspx?sc_lang=en.

ONLINE PUBLICATION

Appendix 1 Panel C: Validation of ProPublica Data with Data Obtained Directly from One Pharmaceutical Company, for One Year

ProPublica assembled data on payments to physicians from 12 pharmaceutical companies, between the third quarter of 2009 and fourth quarter of 2011. This compilation was important because historical data are not easily obtainable from all pharmaceutical companies directly. For example, some companies remove data from their website at the end of each quarter or year.

To partially validate the quality of the ProPublica data, we compared it with data obtained directly from Eli Lilly, for payments made to physicians during 2010. We found a match of $\geq 97.5\%$ for the number of physicians and total amount of payments, in each category and overall. Similarly high match rates were found for Astrazeneca payments made in 2010, GlaxoSmithKline payments made in 2009 Quarters 2 to 4, Johnson & Johnson payments made in 2010, Merck payments made from 2009 Quarter 3 to 2010 Quarter 4, Valeant payments made in 2010 Quarters 1 to 3, and Viiv payments made in 2010. Other data were not reported in a quarterly or yearly time frame available for comparison.

ProPublica data for payments from Eli Lilly during 2010

	Speaking	Consulting	Travel	Other	Total
Number of Physicians	3,727	1,005	3,683	864	9,279
Total Amount (\$)	61,477,547	4,114,517	5,205,539	7,065,820	77,863,092

Data obtained directly from Eli Lilly for payments during 2010

(Eli Lilly and Company. Physician Payment Registry. Q1-Q4 2010 Lilly Faculty Registry. Accessed at <http://www.lillyphysicianpaymentregistry.com/Registry/Archives>, August 30, 2012)

	Speaking	Consulting	Travel	Other	Total
Number of Physicians	3,743	1,016	3,701	867	9,327
Total Amount (\$)	61,925,592	4,218,849	5,232,081	7,092,908	78,469,430

ProPublica data / Data obtained directly from Eli Lilly for payments during 2010

	Speaking	Consulting	Travel	Other	Total
Number of Physicians	99.6%	98.9%	99.5%	99.7%	99.5%
Total Amount (\$)	99.3%	97.5%	99.5%	99.6%	99.2%

Appendix 2. Description of State-level Variables Used as Controls in Regression Analysis

Real Income Per Capita (\$)

Definition: Household income, 2010 / Consumer Price Index [an adjustment for inflation since 2001]

Source: U.S. Department of Commerce, Bureau of Economic Analysis

Rationale: Wealthier people may be more able afford prescription drugs but have fewer health problems (decreasing their need to purchase prescription drugs). Both factors may influence the interest of pharmaceutical companies in associating with physicians in these states.

Average Physician Wage (\$)

Definition: Average physician and surgeon wage, 2010

Source: U.S. Department of Labor, Bureau of Labor Statistics, Occupational and Employment Statistics, Occupational Employment and Wages, 29-1069 Physicians and Surgeons, All Other

Rationale: Physicians earning a higher income may have less need to supplement income through payments from pharmaceutical companies.

Cost of Living Index

Definition: Consumer price index in state, 2010

Source: U.S. Department of Labor, Bureau of Labor Statistics

Rationale: Physicians in states with a higher cost of living may need extra income (e.g., payments from pharmaceutical companies) to meet their expenses.

Population < 18 y (%)

Definition: Population aged <18 years / Total population, 2010

Source: U.S. Census Bureau, Current Population Survey

Rationale: Special considerations may be taken into account when prescribing medications for children

(differential safety, dosage, duration, etc.). These issues may affect the interest of pharmaceutical companies in associating with physicians in states with a large proportion of children.

Population $\geq$ 65 y (%)

Definition: Population aged $\geq$ 65 years / Total population, 2010

Source: U.S. Census Bureau, Current Population Survey

Rationale: States with a large elderly population may have a bigger market share for prescription drugs, increasing the interest of pharmaceutical companies to associate with physicians in these states.

$\geq$ High School Education (%)

Definition: Population with at least a high school education / Total population, 2010

Source: U.S. Census Bureau, Current Population Survey

Rationale: More educated persons may have a higher income, increasing their ability to afford prescription drugs. On the other hand, more educated persons may have fewer health problems, decreasing their need to purchase prescription drugs. Both factors may influence the interest of pharmaceutical companies in associating with physicians in these states.

Health Insurance (%)

Definition: Population aged 18-64 years with health insurance / Total population 18-64 years, 2010

Source: U.S. Census Bureau, Current Population Survey

Rationale: Individuals with health insurance are more likely to be able to afford prescription medications, increasing the interest of pharmaceutical companies to associate with physicians in these states.

Number of Retail Prescriptions Filled at Pharmacies (Person/Year)

Definition: Total number of prescription drugs filled at retail pharmacies in 2011 / Population in 2011.

Source: The Kaiser Family Foundation, statehealthfacts.org. Retail Prescription Drugs Filled at

Pharmacies (Annual per Capita), 2011. Data Source: SDI Health, L.L.C.: Special Data Request, 2012 and Calculations based on U.S. Census Bureau, 2011 Population Estimates, <http://www.census.gov/popest/data/index.html>.

Rationale: Pharmaceutical companies may be more interested in associating with physicians in states with a bigger prescription drug market size.

Additional comments: Kaiser Family Foundation notes that prescription data are based on IMS's Vector One® database which collects data from a panel of retail pharmacies, third party payers, and data providers. "Retail pharmacies" include independent pharmacies, chain pharmacies, food stores, and mass merchandisers, and exclude prescriptions filled by mail order; includes both brand name and generic drugs; and may include a small portion of over-the-counter medications and drugs transferred to different containers solely for distribution purposes.

Population Density (Thousands/Square Mile)

Definition: Total population (thousands), 2010 / Land area of state (square miles)

Source: U.S. Census Bureau, Current Population Survey and Statistical Abstract of the United States

Rationale: In densely populated areas, it may be easier for one physician to influence other physicians (for example, through more interaction with other physicians on a regular basis, whether casual or through well-attended speaking engagements). This may increase the interest of pharmaceutical companies in associating with physicians in more densely populated states.

Number of Physicians with Active Licenses

Definition: Number of physicians with active licenses, 2009-2010

Source: American Medical Association

Rationale: The amount that pharmaceutical companies are willing to pay physicians may be inversely associated with companies' ability to find another physician with similar qualifications. For example, if a pharmaceutical company can only locate one physician in a state with particular qualifications, then it

may be willing to pay that physician \$250. But if a pharmaceutical company can locate five similar physicians, then it may only be willing to pay that physician \$100.

Additional comments: May include physicians who do not regularly practice medicine, such as those with primarily research or administrative responsibilities.

Number of Nurses with Active Licenses

Definition: Number of nurses with active licenses, 2010

Source: American Hospital Association

Rationale: Disclosure data may occasionally contain payments made to nurses. Otherwise similar rationale to the number of physicians with active licenses.

Table 2 also presents summary statistics for these independent variables. States with strong disclosure laws, weak disclosure laws, and no disclosure laws are not observably different on most demographic characteristics. The exceptions are population density, number of active physicians, and number of active nurses. States with strong disclosure laws have greater population density than states with no disclosure laws but less than states with weak disclosure laws. States with strong disclosure laws and no disclosure laws have similar numbers of active physicians and active nurses, while states with weak disclosure laws have more active physicians and nurses.

Appendix 3. Complete Results and Robustness Checks for Table 3 (Relationship Between Disclosure Laws and Payments to Physicians, 2009-2011).

Payments Specified in Logs

Multiple Regression Model	(1)	(2)	(3)	(4)	(5)	(6)*	(7)	(8)	(9)*
Unit of Analysis	State-Year						Physician-Year		
Dependent Variable	Log Annual Payments Per Active Physician (\$)						Log Annual Payments Among Paid Physicians (\$)		
Independent Variable									
Strong Disclosure Laws	-1.309***	-0.898***	-0.923***	-0.992***	-1.029***	-0.488***	0.373***	0.366***	0.101*
P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.0304
(95% CI)	(-1.923, -0.696)	(-1.337, -0.459)	(-1.373, -0.472)	(-1.491, -0.492)	(-1.473, -0.584)	(-0.716, -0.259)	(0.325 - 0.421)	(0.304 - 0.428)	(0.00959 - 0.193)
Weak Disclosure Laws	-0.198	-0.127	-0.249	-0.264*	-0.195*	-0.176	0.205***	-0.0145	-0.0880***
P	0.586	0.540	0.068	0.011	0.029	0.111	<0.001	0.431	<0.001
(95% CI)	(-0.913, 0.518)	(-0.534, 0.281)	(-0.516, 0.0183)	(-0.465, -0.0624)	(-0.369, -0.0207)	(-0.394, 0.0412)	(0.188 - 0.222)	(-0.0505 - 0.0216)	(-0.130 - -0.0458)
Company (Share of Payments; Omitted Company is Allergan)									
AstraZeneca		37.52***	29.06***	3.390	-0.207	2.716		0.502	6.306***
P		<0.001	<0.001	0.444	0.958	0.256		0.432	<0.001
(95% CI)		(17.56, 57.48)	(14.51, 43.60)	(-5.342, 12.12)	(-7.924, 7.511)	(-1.997, 7.429)		(-0.749, 1.752)	(3.589, 9.024)
Cephalon		21.88***	16.81***	5.904*	-1.219	-3.745		0.0428	5.263***
P		<0.001	<0.001	0.0255	0.623	0.0712		0.943	<0.001
(95% CI)		(13.11, 30.65)	(10.86, 22.76)	(0.737, 11.07)	(-6.109, 3.671)	(-7.820, 0.329)		(-1.122, 1.207)	(2.643, 7.883)
EMD Serono		22.11***	16.13***	8.261*	1.626	0.202		10.97***	5.608
P		<0.001	<0.001	0.0122	0.541	0.911		<0.001	0.145
(95% CI)		(9.276, 34.95)	(8.000, 24.26)	(1.830, 14.69)	(-3.625, 6.877)	(-3.359, 3.763)		(4.514, 17.42)	(-1.933, 13.15)
Eli Lilly		76.25	-19.43	-15.06	-3.975	-11.18		-0.287	6.403***
P		0.0702	0.419	0.462	0.821	0.415		0.624	<0.001
(95% CI)		(-6.362, 158.9)	(-66.83, 27.97)	(-55.41, 25.29)	(-38.74, 30.79)	(-38.28, 15.91)		(-1.437, 0.862)	(3.767, 9.040)
GlaxoSmithKline		16.37**	12.36**	5.162	-0.987	0.105		-0.803	5.353***

P	0.00680	0.00107	0.0762	0.717	0.956	0.174	<0.001
(95% CI)	(4.589, 28.14)	(5.053, 19.67)	(-0.552, 10.88)	(-6.355, 4.381)	(-3.637, 3.847)	(-1.961, 0.355)	(2.721, 7.985)
Johnson & Johnson	15.01*	13.50***	5.885*	-0.489	-0.114	-0.775	4.697***
P	0.0138	<0.001	0.0469	0.851	0.949	0.231	<0.001
(95% CI)	(3.104, 26.91)	(6.070, 20.94)	(0.0825, 11.69)	(-5.648, 4.670)	(-3.643, 3.416)	(-2.044, 0.493)	(2.011, 7.383)
Merck	35.37***	30.53***	7.092	-0.835	3.681	-1.979**	5.355***
P	<0.001	<0.001	0.141	0.830	0.440	0.00682	<0.001
(95% CI)	(16.68, 54.07)	(18.78, 42.28)	(-2.374, 16.56)	(-8.537, 6.867)	(-5.731, 13.09)	(-3.413, -0.545)	(2.457, 8.253)
Novartis	12.81*	14.19***	3.580	-1.265	0.242	-0.0493	5.793***
P	0.0204	<0.001	0.229	0.649	0.896	0.948	<0.001
(95% CI)	(2.010, 23.62)	(6.808, 21.58)	(-2.278, 9.438)	(-6.745, 4.216)	(-3.402, 3.885)	(-1.541, 1.443)	(2.915, 8.672)
Pfizer	21.59**	19.34***	4.409	-1.083	-0.578	-0.328	5.484***
P	0.00409	<0.001	0.211	0.699	0.783	0.575	<0.001
(95% CI)	(6.967, 36.21)	(9.639, 29.03)	(-2.531, 11.35)	(-6.621, 4.456)	(-4.727, 3.571)	(-1.474, 0.818)	(2.854, 8.114)
Valeant	18.94**	14.34***	6.759*	0.0621	0.236	0.954	7.022**
P	0.00170	<0.001	0.0243	0.982	0.898	0.631	0.00329
(95% CI)	(7.238, 30.63)	(6.868, 21.82)	(0.891, 12.63)	(-5.255, 5.379)	(-3.408, 3.879)	(-2.933, 4.841)	(2.340, 11.70)
ViiV	52.35*	14.98	17.93	3.537	2.438	0.565	6.815***
P	0.0417	0.370	0.131	0.649	0.767	0.554	<0.001
(95% CI)	(1.999, 102.7)	(-17.99, 47.94)	(-5.404, 41.27)	(-11.83, 18.90)	(-13.87, 18.75)	(-1.307, 2.436)	(3.797, 9.832)
Category (Share of Payments; Omitted Category is Consulting)							
Items		-29.68*	-28.29***	-12.05*	-2.768	-13.61***	-17.92***
P		0.0306	<0.001	0.0301	0.663	<0.001	<0.001
(95% CI)		(-56.54, -2.816)	(-41.59, -15.00)	(-22.93, -1.181)	(-15.33, 9.798)	(-16.02, -11.19)	(-21.42, -14.42)
Meals		8.018***	4.319*	3.330*	2.972**	1.067***	-2.869*
P		<0.001	0.0191	0.0277	0.00898	<0.001	0.0183
(95% CI)		(4.889, 11.15)	(0.719, 7.918)	(0.371, 6.288)	(0.759, 5.184)	(0.599, 1.534)	(-5.251, -0.486)
Other		-2.197	-0.845	-3.130*	0.763	0.538	-5.491***
P		0.281	0.652	0.0473	0.535	0.158	<0.001
(95% CI)		(-6.212, -)	(-4.550, -)	(-6.223, -)	(-1.666, -)	(-0.208, -)	(-8.115, -)

		1.819)	2.859)	0.0373)	3.192)	1.284)	2.866)
Research		1.482	-0.627	-1.413	1.283	1.282***	-4.665***
P		0.162	0.543	0.146	0.0997	<0.001	<0.001
(95% CI)		(-0.602,	(-2.660,	(-3.324,	(-0.249,	(0.943,	(-7.071, -
		3.566)	1.407)	0.498)	2.814)	1.621)	2.258)
Speaking		-0.713	-0.666	-1.850*	-0.376	1.527***	-5.115***
P		0.516	0.475	0.0201	0.707	<0.001	<0.001
(95% CI)		(-2.879,	(-2.508,	(-3.405, -	(-2.358,	(1.172,	(-7.548, -
		1.453)	1.175)	0.295)	1.606)	1.882)	2.683)
Travel		-2.654	-9.825**	-6.686*	-0.499	1.177*	-3.630**
P		0.465	0.00528	0.0478	0.814	0.0134	0.00574
(95% CI)		(-9.821,	(-16.68, -	(-13.31, -	(-4.699,	(0.244,	(-6.206, -
		4.513)	2.975)	0.0654)	3.701)	2.110)	1.055)
Year (Relative to payments in 2011)							
2009			-1.556***	-1.305***	-0.406	4.800***	2.276***
P			<0.001	<0.001	0.627	<0.001	<0.001
(95% CI)			(-2.466, -	(-2.015, -	(-2.061,	(4.681,	(1.765,
			0.646)	0.595)	1.248)	4.919)	2.786)
2010			1.108***	1.038***	0.819	0.818***	0.407***
P			<0.001	<0.001	0.315	<0.001	<0.001
(95% CI)			(0.603,	(0.641,	(-0.790,	(0.745,	(0.264,
			1.613)	1.435)	2.429)	0.891)	0.549)
Demographics							
Household Income				2.10e-05	-1.09e-05	2.01e-06	7.90e-06*
(\$)							
P				0.177	0.538	0.432	0.0102
(95% CI)				(-9.61e-06,	(-4.58e-	(-3.00e-06,	(1.87e-06,
				5.16e-05)	05, 2.41e-	7.01e-06)	1.39e-05)
					05)		
Average Physician				-2.03e-06	-2.06e-07	5.04e-07*	3.30e-07
Wage (\$)							
P				0.0679	0.809	0.0144	0.125
(95% CI)				(-4.21e-06,	(-1.89e-	(1.00e-07,	(-9.14e-08,
				1.52e-07)	06, 1.48e-	9.07e-07)	7.52e-07)
					06)		
Cost of Living Index				-0.000647	-0.00129	0.00366***	0.00346***
P				0.808	0.524	<0.001	<0.001
(95% CI)				(-0.00591,	(-0.00531,	(0.00279,	(0.00238,
				0.00462)	0.00272)	0.00453)	0.00454)
% Population < 18 y				9.842***	1.443	-1.615***	0.720

P	<0.001	0.619	0.000493	0.182
(95% CI)	(4.709, 14.97)	(-4.297, 7.182)	(-2.524, 0.707)	(-0.339, 1.779)
% Population ≥ 65 y	4.350	-0.154	-0.282	-3.176**
P	0.0804	0.939	0.478	0.00113
(95% CI)	(-0.535, 9.234)	(-4.145, 3.837)	(-1.059, 0.496)	(-5.088, 1.265)
% Unemployment	0.0210	0.0282	0.00562**	0.00583*
P	0.0673	0.404	0.00696	0.0180
(95% CI)	(-0.00152, 0.0436)	(-0.0385, 0.0948)	(0.00154, 0.00970)	(0.00100, 0.0107)
% ≥ High School Education	-0.996	-1.875	-1.425***	-0.773***
P	0.382	0.0695	<0.001	<0.001
(95% CI)	(-3.245, 1.253)	(-3.902, 0.152)	(-1.838, 1.012)	(-1.201, 0.344)
% Health Insurance	0.894	1.202	0.0692	0.296
P	0.160	0.0562	0.512	0.205
(95% CI)	(-0.358, 2.145)	(-0.0324, 2.437)	(-0.138, 0.276)	(-0.161, 0.753)
Annual Prescription Drugs Filled at Pharmacies/Person	0.0849***	0.0251	-0.0119***	0.0975***
P	<0.001	0.439	<0.001	<0.001
(95% CI)	(0.0455, 0.124)	(-0.0390, 0.0891)	(-0.0182, 0.00561)	(0.0686, 0.127)
Population Density	1.09e-05	0.000463*	-6.38e-07	3.72e-05**
P	0.743	0.0150	0.938	0.00505
(95% CI)	(-5.47e-05, 7.65e-05)	(9.18e-05, 0.000835)	(-1.68e-05, 1.55e-05)	(1.12e-05, 6.32e-05)
Number of Active Physicians	-9.23e-06	-3.88e-06	-1.19e-06	-2.03e-06
P	0.166	0.562	0.358	0.147
(95% CI)	(-2.23e-05, 3.87e-06)	(-1.71e-05, 9.37e-06)	(-3.71e-06, 1.34e-06)	(-4.77e-06, 7.14e-07)
Number of Active Nurses	3.45e-06	1.35e-06	9.10e-07*	1.56e-06**
P	0.139	0.567	0.0453	0.00144
(95% CI)	(-1.14e-06, 8.04e-06)	(-3.33e-06, 6.04e-06)	(1.92e-08, 1.80e-06)	(6.00e-07, 2.52e-06)

LASSO (see Appendix 2)	-	-	-	-	-	Yes	-	-	Yes
N	153	153	153	153	153	153	425,787	425,787	425,787
R ²	0.062	0.862	0.924	0.952	0.974	0.990	0.002	0.207	0.215
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Denotes model shown in Table 3.

* P<0.05, **P<0.01, ***P<0.001.

Appendix 4. Complete Results for Figure 1 (Relationship Between Disclosure Laws and Category of Payments, State Level, 2009-2011).

Dependent Variable: Payment Amounts in Each Category as a Percent of Total Payments in Each State and Year

Multiple Regression Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Consulting	Speaking	Research	Meals	Travel	Items	Other
Independent Variable							
Strong Disclosure Laws	0.0943***	-0.105**	0.0558	-0.0306*	0.00157	-0.00103	-0.0154
P	<0.001	0.00149	0.118	0.0146	0.779	0.485	0.116
(95% CI)	(0.0491, 0.140)	(-0.169, -0.0409)	(-0.0143, 0.126)	(-0.0550, -0.00614)	(-0.00950, 0.0127)	(-0.00396, 0.00189)	(-0.0347, 0.00385)
Weak Disclosure Laws	-0.0212*	0.0281	-0.0297	0.0277*	-0.00488	0.000355	-0.000336
P	0.0217	0.245	0.262	0.0261	0.181	0.818	0.962
(95% CI)	(-0.0393, -0.00316)	(-0.0196, 0.0758)	(-0.0819, 0.0225)	(0.00335, 0.0521)	(-0.0121, 0.00230)	(-0.00269, 0.00340)	(-0.0143, 0.0136)
Company (Share of Payments; Omitted Company is Allergan)							
AstraZeneca	-0.0609	-0.258	-0.513	-0.189	0.227	-0.0158	-0.189
P	0.904	0.858	0.700	0.625	0.149	0.888	0.445
(95% CI)	(-1.060, 0.939)	(-3.117, 2.600)	(-3.143, 2.116)	(-0.952, 0.574)	(-0.0823, 0.536)	(-0.237, 0.206)	(-0.678, 0.300)
Cephalon	0.263	0.883	-1.004	-0.117	0.204*	-0.00434	-0.225
P	0.394	0.421	0.275	0.561	0.0437	0.946	0.140
(95% CI)	(-0.346, 0.873)	(-1.280, 3.046)	(-2.817, 0.810)	(-0.516, 0.281)	(0.00580, 0.401)	(-0.132, 0.123)	(-0.524, 0.0744)
EMD Serono	0.223	0.0238	-0.259	-0.258	0.353**	-0.0429	-0.0391
P	0.512	0.983	0.784	0.243	0.00110	0.506	0.793
(95% CI)	(-0.449, 0.895)	(-2.128, 2.176)	(-2.128, 1.610)	(-0.694, 0.178)	(0.144, 0.561)	(-0.170, 0.0843)	(-0.333, 0.255)
Eli Lilly	3.472	-3.644	-6.381	4.360	-0.326	0.288	2.231
P	0.239	0.536	0.445	0.116	0.808	0.232	0.0910
(95% CI)	(-2.339, 9.283)	(-15.25, 7.964)	(-22.85, 10.09)	(-1.085, 9.805)	(-2.980, 2.328)	(-0.187, 0.763)	(-0.361, 4.823)
GlaxoSmithKline	0.293	0.0182	-0.0216	-0.342	0.306**	-0.0679	-0.186
P	0.371	0.987	0.982	0.118	0.00338	0.301	0.218

	(95% CI)	(-0.352, 0.937)	(-2.161, 2.198)	(-1.885, 1.842)	(-0.772, 0.0883)	(0.103, 0.509)	(-0.197, 0.0614)	(-0.482, 0.111)
	Johnson & Johnson P	0.279	0.232	-0.174	-0.264	0.283**	-0.0613	-0.294
	(95% CI)	0.390	0.834	0.853	0.228	0.00607	0.354	0.0549
	(95% CI)	(-0.361, 0.919)	(-1.954, 2.417)	(-2.039, 1.690)	(-0.696, 0.167)	(0.0824, 0.484)	(-0.192, 0.0690)	(-0.594, 0.00629)
	Merck P	0.266	1.633	-1.624	-0.500	0.663***	-0.164	-0.274
	(95% CI)	0.622	0.262	0.225	0.115	<0.001	0.0715	0.295
	(95% CI)	(-0.800, 1.332)	(-1.234, 4.499)	(-4.258, 1.010)	(-1.123, 0.124)	(0.307, 1.020)	(-0.343, 0.0146)	(-0.791, 0.242)
	Novartis P	0.219	1.054	-1.097	-0.296	0.374***	-0.0558	-0.198
	(95% CI)	0.526	0.353	0.250	0.163	<0.001	0.389	0.235
	(95% CI)	(-0.461, 0.899)	(-1.184, 3.291)	(-2.974, 0.780)	(-0.713, 0.122)	(0.184, 0.565)	(-0.183, 0.0719)	(-0.527, 0.130)
	Pfizer P	-0.0386	0.631	-0.441	-0.0524	0.252	0.0257	-0.376
	(95% CI)	0.917	0.605	0.688	0.845	0.0951	0.738	0.0782
	(95% CI)	(-0.774, 0.697)	(-1.778, 3.039)	(-2.614, 1.732)	(-0.582, 0.477)	(-0.0445, 0.549)	(-0.126, 0.178)	(-0.795, 0.0430)
	Valeant P	0.262	0.222	-0.371	-0.208	0.387***	-0.0596	-0.232
	(95% CI)	0.418	0.839	0.691	0.338	<0.001	0.357	0.127
	(95% CI)	(-0.376, 0.900)	(-1.937, 2.381)	(-2.211, 1.469)	(-0.638, 0.221)	(0.188, 0.586)	(-0.187, 0.0681)	(-0.532, 0.0673)
	ViiV P	3.026	-4.224*	1.230	0.592	0.0748	-0.248	-0.450
	(95% CI)	0.162	0.0469	0.617	0.749	0.927	0.118	0.449
	(95% CI)	(-1.236, 7.288)	(-8.388, -0.0594)	(-3.622, 6.081)	(-3.065, 4.248)	(-1.535, 1.684)	(-0.561, 0.0641)	(-1.624, 0.723)
	Year (Relative to payments in 2011)							
	2009	0.0561*	0.339***	-0.441***	-0.0526***	-0.0238**	0.000926	0.121***
	P	0.0172	<0.001	<0.001	<0.001	0.00118	0.791	<0.001
	(95% CI)	(0.0101, 0.102)	(0.242, 0.437)	(-0.541, -0.340)	(-0.0818, -0.0235)	(-0.0380, -0.00962)	(-0.00598, 0.00783)	(0.0933, 0.148)
	2010	0.0474	0.00784	-0.0782	-0.0320	-0.0105	0.00330	0.0621***
	P	0.112	0.897	0.189	0.0757	0.207	0.363	<0.001
	(95% CI)	(-0.0111, 0.106)	(-0.111, 0.127)	(-0.195, 0.0390)	(-0.0674, 0.00335)	(-0.0269, 0.00588)	(-0.00386, 0.0105)	(0.0336, 0.0906)
Demographics								

Household Income (\$)	5.00e-06	-1.84e-06	4.14e-07	-1.70e-06	-8.92e-07	-5.81e-07*	-4.25e-07
P	0.0599	0.669	0.931	0.266	0.295	0.0129	0.714
(95% CI)	(-2.12e-07, 1.02e-05)	(-1.03e-05, 6.65e-06)	(-9.07e-06, 9.89e-06)	(-4.72e-06, 1.31e-06)	(-2.57e-06, 7.88e-07)	(-1.04e-06, -1.25e-07)	(-2.72e-06 - 1.87e-06)
Average Physician Wage (\$)	-1.12e-07	2.79e-07	-2.03e-07	2.21e-08	4.64e-08	1.91e-08	7.49e-05
P	0.459	0.324	0.491	0.828	0.413	0.185	0.632
(95% CI)	(-4.10e-07, 1.86e-07)	(-2.79e-07, 8.37e-07)	(-7.83e-07, 3.78e-07)	(-1.79e-07, 2.23e-07)	(-6.53e-08, 1.58e-07)	(-9.25e-09, 4.75e-08)	(-0.000234 - 0.000384)
Cost of Living Index	-0.000524	0.000826	-0.00167*	0.00119***	-4.67e-05	0.000137*	0.000435
P	0.0619	0.138	0.0169	<0.001	0.575	0.0219	0.677
(95% CI)	(-0.00107, 2.64e-05)	(-0.000268, 0.00192)	(-0.00303, -0.000304)	(0.000523, 0.00186)	(-0.000211, 0.000118)	(2.01e-05, 0.000253)	(-0.00163 - 0.00250)
% Population < 18 y	-0.0921	-0.706	0.855	0.0914	-0.180	-0.0606	0.103
P	0.855	0.334	0.293	0.655	0.139	0.115	0.321
(95% CI)	(-1.091, 0.907)	(-2.147, 0.736)	(-0.747, 2.457)	(-0.313, 0.495)	(-0.419, 0.0590)	(-0.136, 0.0150)	(-0.101 - 0.306)
% Population ≥ 65 y	0.167	-0.959	1.349	-0.312	-0.162	-0.143*	-0.0193
P	0.704	0.236	0.132	0.164	0.158	0.0342	0.721
(95% CI)	(-0.701, 1.035)	(-2.552, 0.634)	(-0.411, 3.109)	(-0.753, 0.129)	(-0.389, 0.0641)	(-0.274, -0.0108)	(-0.126 - 0.0872)
% Unemployment	0.00175	-0.000553	-0.000200	-0.000849	-0.000140	-	0.00132
P	0.360	0.878	0.960	0.431	0.801	0.000472**	0.324
(95% CI)	(-0.00201, 0.00551)	(-0.00767, 0.00656)	(-0.00798, 0.00758)	(-0.00298, 0.00128)	(-0.00124, 0.000957)	(-0.000825, -0.000120)	(-0.00132 - 0.00396)
% ≥ High School Education	-0.154	-0.244	0.0740	0.111	0.0501	0.0555	0.0769
P	0.429	0.502	0.840	0.300	0.400	0.0592	0.707
(95% CI)	(-0.538, 0.230)	(-0.962, 0.473)	(-0.652, 0.800)	(-0.100, 0.322)	(-0.0674, 0.168)	(-0.00220, 0.113)	(-0.327 - 0.481)
% Health Insurance	0.0220	0.228	-0.0827	-0.163**	0.0475	-0.0317	0.0470
P	0.815	0.202	0.655	0.00821	0.0857	0.0570	0.815

(95% CI)	(-0.164, 0.208)	(-0.124, 0.580)	(-0.448, 0.283)	(-0.283, -0.0429)	(-0.00677, 0.102)	(-0.0643, 0.000954)	(-0.350 - 0.444)
Annual Prescription Drugs Filled at Pharmacies/Person	-0.000817	0.00381	-0.00511	0.00101	-0.000225	-3.02e-05	1.47e-07
P	0.770	0.416	0.295	0.512	0.798	0.926	0.952
(95% CI)	(-0.00633, 0.00470)	(-0.00544, 0.0131)	(-0.0147, 0.00452)	(-0.00203, 0.00406)	(-0.00196, 0.00151)	(-0.000669, 0.000609)	(-4.65e-06 - 4.95e-06)
Population Density	5.75e-06	-8.14e-06	9.20e-06	-9.00e-06**	2.65e-06*	-4.16e-07	-4.02e-07
P	0.0904	0.557	0.442	0.00217	0.0113	0.414	0.560
(95% CI)	(-9.20e-07, 1.24e-05)	(-3.55e-05, 1.92e-05)	(-1.44e-05, 3.28e-05)	(-1.47e-05, -3.31e-06)	(6.12e-07, 4.70e-06)	(-1.42e-06, 5.87e-07)	(-1.76e-06 - 9.57e-07)
Number of Active Physicians	1.91e-06	-3.91e-06	4.81e-06	-2.77e-06***	6.90e-07	-3.09e-07	1.51e-07
P	0.0628	0.105	0.0553	0.000550	0.0507	0.0804	0.540
(95% CI)	(-1.03e-07, 3.92e-06)	(-8.66e-06, 8.29e-07)	(-1.11e-07, 9.74e-06)	(-4.32e-06, -1.22e-06)	(-2.22e-09, 1.38e-06)	(-6.56e-07, 3.79e-08)	(-3.34e-07 - 6.35e-07)
Number of Active Nurses	-6.04e-07	1.26e-06	-1.52e-06	8.60e-07**	-2.49e-07*	9.80e-08	-5.58e-08
P	0.103	0.129	0.0715	0.00234	0.0458	0.107	0.541
(95% CI)	(-1.33e-06, 1.24e-07)	(-3.69e-07, 2.89e-06)	(-3.18e-06, 1.35e-07)	(3.12e-07, 1.41e-06)	(-4.94e-07, -4.72e-09)	(-2.15e-08, 2.17e-07)	(-2.36e-07 - 1.24e-07)
N	153	153	153	153	153	153	153
R ²	0.617	0.871	0.866	0.825	0.738	0.685	0.855
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

* P<0.05, **P<0.01, ***P<0.001

Appendix 5: Relationship Between Disclosure Laws and Distribution of Payments to Physicians, 2009-2011.*

Multiple Regression Model	(1)	(2)	(3)	(4)
Unit of Analysis	Physician-Year	State-Year	Physician-Year	State-Year
Dependent Variable	Annual Payments Among Physicians ≤\$100/yr	Number of Physicians Accepting ≤\$100/yr	Annual Payments Among Physicians >\$100/yr	Number of Physicians Accepting >\$100/yr
Units	Log \$	Log	Log \$	Log
Independent Variable				
Disclosure Laws With Public Reporting (“Strong”)		-0.676*		-0.396
P	-0.0192	0.0322	0.543***	0.0528
(95% CI)	(-0.0910, 0.0526)	(-1.294, -0.0588)	(0.411, 0.674)	(-0.796, 0.00495)
Disclosure Laws Without Public Reporting (“Weak”)		-0.303		-0.483**
P	0.0498***	0.150	0.0363	0.00581
(95% CI)	(0.0222, 0.0774)	(-0.718, 0.112)	(-0.0387, 0.111)	(-0.823, -0.143)
N	286768	153	139019	153
R ²	0.054	0.989	0.172	0.958

*Adjusted for company providing payment, category of payment, year, and statewide demographics.

Appendix 6: Relationship Between Disclosure Laws and Payments, Differences-in-Differences, 2009-2011.*

Dependent Variable: Payment Amounts Total and in Each Category as a Percent of Total Payments in Each State and Year

Differences-in-Differences Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Annual Payment Per Active Physician	Research	Consulting	Meals	Travel	Speaking	Items	Other
Units	Log \$	%	%	%	%	%	%	%
Independent Variable								
Massachusetts P (95% CI)	0.150*** <0.001 (0.113 - 0.186)	0.143*** <0.001 (0.128 - 0.157)	0.176*** <0.001 (0.173 - 0.180)	-0.0899*** <0.001 (-0.0941 - -0.0857)	0.0378*** <0.001 (0.0355 - 0.0402)	-0.195*** <0.001 (-0.205 - -0.186)	-0.0277*** <0.001 (-0.0282 - -0.0271)	-0.0310*** <0.001 (-0.0333 - -0.0287)
Massachusetts * Year > 2010 P (95% CI)	-0.356*** <0.001 (-0.465 - -0.247)	0.0865*** <0.001 (0.0436 - 0.129)	0.0105* 0.0486 (6.63e-05 - 0.0209)	-0.0422*** <0.001 (-0.0548 - -0.0296)	-0.0197*** <0.001 (-0.0268 - -0.0126)	-0.0702*** <0.001 (-0.0985 - -0.0419)	-0.00133 0.128 (-0.00306 - 0.000396)	0.0322*** <0.001 (0.0253 - 0.0392)
N	153	153	153	153	153	153	153	153

*Adjusted for dummy indicators for each state and year.

Appendix 7. Relationship Between Disclosure Laws and Payments to Physicians, 2009-2011.*

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unit of Analysis	State-Year	Physician-Year	Physician-Year	Physician-Year	{ Difference in Payments Between MA and All Other States, Before and After Public Release of MA Payments }		
Dependent Variable	Log Annual Payments Per Active Physician	Log Annual Payments Among Paid Physicians	Log Annual Payments Among Physicians Who Accepted >\$100	Log Annual Payments Among Physicians Who Accepted ≤\$100**	Log Annual Payments Per Active Physician	Log Annual Payments Among Physicians Who Accepted >\$100	Log Annual Payments Among Physicians Who Accepted ≤\$100**
Independent Variable							
Disclosure Laws With Public Reporting (“Strong”)	-0.488***	0.101	1.785*	-0.255***			
P	<0.001	0.188	0.0236	<0.001			
(95% CI)	(-0.698, -0.277)	(-0.0512, 0.254)	(0.239, 3.331)	(-0.301, -0.208)			
Disclosure Laws Without Public Reporting (“Weak”)	-0.176	-0.0880	0.506	-0.0614			
P	0.104	0.0551	0.386	0.321			
(95% CI)	(-1.254, 8.852)	(-0.178, 0.00198)	(-0.638, 1.650)	(-0.183, 0.0598)			
Massachusetts x After Public Release in MA					-0.356***	8.503***	-0.0685***
P					<0.001	<0.001	<0.001
(95% CI)					(-0.465, -0.247)	(5.611, 11.39)	(-0.0841, -0.0530)
N	153	425,797	139,019	2,257,059	153	141,736	2,257,059
R ²	0.99	0.215			0.972		

*Adjusted for company providing payment, category of payment, year, and statewide demographics. Demographics are household income, average physician wage, cost of living, % population < 18, % population ≥ 65, % unemployment, % ≥ high school education, % health insurance, annual prescription drugs filled at pharmacies/person, population density, number of active physicians, and number of active nurses. Full results displayed in Appendix 3. Additional LASSO controls in Appendix 8. Standard errors clustered at the state level. Columns 3, 4, 6, and 7 implement truncated regressions.

**Included a zero for physicians who accepted no payments.

Appendix 8 LASSO variables

Annual Physician Mean Wage	Number of Paid Physicians
% Unemployment	Number of Physicians
Physicians Per Capita	Number of Nurses
Population	Land Area
Population Density	Percent Under 18
Percent Over 65	Cost of Living Index
Prescribed Drugs Per Capita	Adoption Rate
Percent of Women Aged 25-29	Percent of Women Aged 30-34
Percent Hispanic	Percent Non-Hispanic
Percent Insured	Percent of Women Working
High School Completion	Income Per Capita
Percent in Large Firms	Raw Consumer Price Index
Consumer Price Index	Real Income Per Capita
% Payments from each Company by Value and by Count	% Payments in each Payment Category by Value and by Count
Year Fixed Effects	All two-way interactions between any of these variables

Variables selected by LASSO for state-level regressions

Number of Paid Physicians * % Payments by Count for Cephalon	Unemployment Rate * % Payments by Count from Pfizer
Number of Paid Physicians * % Payments by Value for Items	% Payments by Count from Cephalon * % Payments by Count from Pfizer
Percent Under 18 * % Payments by Count for Meals	% Payments by Count from Eli Lilly * % Payments by Value for Speaking
Cost of Living Index * % Payments by Count for Consulting	% Payments by Count from Pfizer * % Payments by Count for Meals
Prescribed Drugs Per Capita * Percent of Women Aged 25-29	% Payments by Count for Meals * % Payments by Value for Speaking
Prescribed Drugs Per Capita * % Payments by Value from AstraZeneca	% Payments by Count for Meals * Year 2010 Fixed Effect
Prescribed Drugs Per Capita * % Payments by Value from Johnson & Johnson	% Payments by Value for Research * Year 2010 Fixed Effect
Prescribed Drugs Per Capita * % Payments by Count for Meals	Employment Rate * % Payments by Value for Consulting
Annual Physician Mean Wage * % Payments by Count for Speaking	Physicians Per Capita * % Payments by Count for Research
Percent in Large Firms * % Payments by Count from Pfizer	Population Density * Population Density

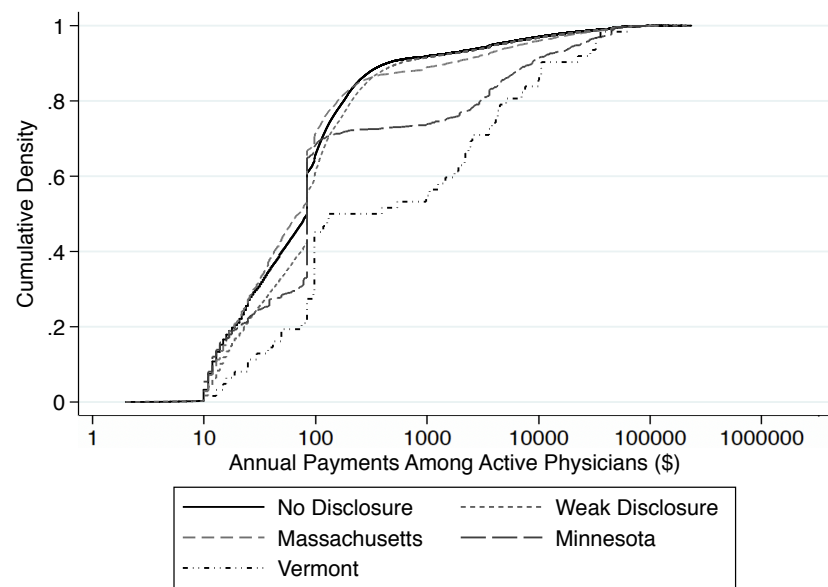
Variables selected by LASSO for paid physician-level regressions

% Payments by Count for Speaking	Cost of Living Index * % Payments by Count for Speaking
Physicians Per Capita * % Payments by Count for Other	Drugs Per Capita * % Payments by Count for Meals
Percent Over 65 * % Payments by Count for Meals	Drugs Per Capita * % Payments by Count for Other
Cost of Living Index * % Payments by Count for Consulting	Drugs Per Capita * Year 2011 Fixed Effect
Adoption Rate * % Payments by Count for Consulting	Percent Insured * % Payments by Count for Meals
Percent in Large Firms * % Payments by Count for Meals	% Unemployment * % Payments by Count from Merck
% Unemployment * % Payments by Count for Consulting	% Unemployment * % Payments by Count for Speaking
% Payments by Count from Cephalon * % Payments by Count for Meals	% Payments by Value from Eli Lilly * % Payments by Count for Meals
Physicians Per Capita * % Payments by Value for Consulting	Drugs Per Capita * % Payments by Value for Consulting
Number of Paid Physicians * % Payments by Value from Valeant	

Variables selected by LASSO for physician-level regressions

Real Income Per Capita * Year 2009 Fixed Effect	% Unemployment * Number of Nurses
Drugs Per Capita * Percent Under 18	Drugs Per Capita * Year 2009 Fixed Effect
% Unemployment * Year 2009 Fixed Effect	Drugs Per Capita * Year 2010 Fixed Effect
% Unemployment * Year 2010 Fixed Effect	

Appendix 9. Cumulative Density of Payments To Physicians Who Accepted Payments (\$), 2009-2011.



APPENDIX 10: MODEL

This section seeks to understand why disclosure laws may have behavioral effects. The following is a simple model of the potential impact of disclosure law on physician payments. First, the payoff to paid physicians is predicted to increase after mandatory disclosure because of the reputational cost to physicians of having their industry-physician relationships be made public. Second, physicians receiving low payments drop out with mandatory disclosure because it is not worth it to the pharmaceutical companies to continue paying these physicians. We illustrate the intuition in a two-type model and then a full model with continuous types.

On a theoretical level, our paper contributes to a literature on expert advisors. Many papers have modeled the reputational concerns of expert advisors (Sobel 1985, Benabou and Laroque 1992, Morris 2001), but only two previous models, as far as we are aware, examine the effects of mandatory disclosure (Li and Madarász 2008; Inderst and Ottaviani 2012). Li and Madarász (2008) examines the effect of mandatory disclosure on the advice of experts, whereas we model the effect of mandatory disclosure on the disclosed activity. Our model makes a technical contribution by bounding the reduction in information rent accruing to remaining agents when less efficient agents are shut down in an adverse selection model where outside opportunities increase. We show that raising the opportunity cost of agents in an adverse selection model unambiguously raises the payment to all types who still receive payments. Inderst and Ottaviani (2012) present a different model where firms' commissions (payments) to intermediaries steer the advice of intermediaries and attract customers, but mandatory disclosure stifles all payments because it reduces customers' willingness to pay. However, Inderst and Ottaviani (2012) does not predict mandatory disclosure to increase payments among those already receiving large payments. Our paper also contributes to a large, primarily informal, mandatory disclosure literature in law (Ben-Shahar and Schneider 2014), accounting (Leuz and Verrecchia 2000), and lobbying. A related paper models the effects of third-party funding on the reputation of experts and, like this paper, tests the model using confidential data (Chen 2015).

Two Types

Suppose θ measures the effectiveness of a physician in increasing pharmaceutical company sales. For example, scientific thought leaders may be more successful at conducting clinical research or more effective at presenting the results of clinical research or simply be more behaviorally responsive to payments. The overall output also depends on effort e put forth by the physician, such that the physician succeeds at persuading others with probability $p(e)$ and fails with probability $1 - p(e)$. As standard in the literature, we assume that the payoff function is concave in e ($p' > 0$ and $p'' < 0$). When the project (or presentation) is successful, the payoff is θ , and 0 otherwise. The overall payoff is then given by:

$$Y = \theta p(e)$$

The distribution of θ depends on the type of physician. Assume there are two types (denoted by p and n), with θ distributions: $F_p(\theta)$ and $F_n(\theta)$, respectively. These distributions capture the intuition that thought leaders, denoted by p are more likely to have larger influence. That is, we assume that $F_p(\theta)$ stochastically dominates

$F_n(\theta)$, in a sense that some physicians are more effective than others at helping the pharmaceutical companies reach their goals:

$$F_p(\theta) \leq F_n(\theta)$$

Exerting effort e costs the physician $c(e)$ with standard assumption of convex costs: $c'(e) > 0$, and $c''(e) > 0$. The physician has the outside option of $\bar{u}$. If the payment to the doctor is w , then the payoff structure needs to satisfy the individual rationality (IR) constraint:

$$w - c(e) \geq \bar{u}$$

Moreover, we specify that transfers cannot go the opposite way: $w \geq 0$.

The pharmaceutical company's objective, for a given physician type, is to maximize the payoff function:

$$\max_{(w)} \theta p(\tilde{e}) - w$$

subject to,

$$e \in \arg \max_{\tilde{e}} \{w - c(\tilde{e})\}$$

$$w - c(e) \geq \bar{u}$$

If we assume that there is no informational asymmetry, i.e., that effort is contractible (this assumption is relaxed in the following section), the First Best solution would involve maximizing the entire surplus:

$$e^* \in \arg \max_{\tilde{e}} \{\theta p(e) - c(\tilde{e})\}$$

and

$$w = c(e^*) + \bar{u}$$

The First Order Condition will be:

$$\theta p'(e^*) = c'(e^*)$$

$$e^* = e^*(\theta)$$

where $e^{*'} > 0$. Thus, the payoff to the pharmaceutical company will be: $\theta p(e^*) - c(e^*) - \bar{u}$. Suppose, θ_0 is the cutoff for non-negative profits:

$$\theta_0 p(e(\theta_0)) - c(e(\theta_0)) - \bar{u} = 0$$

Then, the proportion of doctors that gets paid will be $1 - F(\theta_0)$, and the average wage will be:

$$E(w) = \int_{\theta > \theta_0} [c(e^*(\theta)) + \bar{u}] dF = \int_{\theta > \theta_0} c(e^*(\theta)) dF + (1 - F(\theta_0)) \bar{u}$$

Since F_p stochastically dominates F_n , it is easy to show that:

$$E_p(w) \geq E_n(w)$$

Thus, physicians who are the p types are paid more than physicians who are the n types.

Now, consider the effect of disclosure. We assume that disclosure law increases the cost of each physician for being associated with the pharmaceutical company. Disclosure increases their outside utility, $\bar{u}$, effectively making them more reluctant to accept payments. The reputational cost of accepting payments is passed onto the pharmaceutical company in terms of requiring higher payments to achieve the same effort. The new participation constraint becomes:

$$w = c(e^*) + \bar{u} + \alpha$$

where α is the added cost of disclosure. The new setup does not change the optimal First Order Condition, but will raise the cutoff value, θ'_0 :

$$\theta'_0 p(e(\theta'_0)) - c(e(\theta'_0)) = \bar{u} + \alpha$$

Then, mandatory disclosure has two effects. First, mandatory disclosure increases the payoffs to the paid physicians, because for a given physician effort, the payment to physician increases. Second, mandatory disclosure increases the cutoff threshold for physician effectiveness. The pharmaceutical company will choose not to pay physicians who are less effective than this cutoff. So, mandatory disclosure causes low payments to drop out.

Model with Continuous Types

We now present a model with continuous types and relax the assumption of no information asymmetry. Physician's type θ , with $\theta \in \Theta = [\underline{\theta}, \bar{\theta}] \subset R^+$, measures her effectiveness in increasing company sales. The types are distributed according to the cumulative distribution function $F(\theta)$, and density function $f(\theta) > 0$ in the interval $[\underline{\theta}, \bar{\theta}]$. The pharmaceutical company effectively hires and pays physicians to increase prescription sales by q , which increase revenues by $R(q)$. Assume that $R' > 0, R'' < 0$, and $R(0) = 0$. Physician's type θ specifies her marginal cost of increasing revenues: the low types can generate sales of q more efficiently, at a lower overall cost to themselves, than the high types. The overall cost for the physician will be: $C(q) = \theta q + F$, where F is the fixed cost.

In the general setting, the pharmaceutical company observes the sales quantity generated by physician q , and pays transfer t for the services. The transfers may take the form of direct payments for certain services, such as speaking or consulting engagements, or may cover expenses like travel and conference. Physicians agree and

enter into contract with the pharmaceutical companies, if the level of transfers satisfies their individual rationality constraint. With an outside option of $\bar{u}$, the participation constraint means:

$$t - C(q) \geq \bar{u}$$

The pharmaceutical company maximizes (expected) profits: $R(q) - t$. Below we analyze the situation where the pharmaceutical company also observes the physician type θ (First Best), and when the company doesn't observe the type, and can only contract on quantities (Second Best).

First Best

Under the First Best setup, the pharmaceutical company observes both the quantity produced, as well as the type of physician. The optimal solution maximizes the entire surplus of production:

$$q^* \in \arg \max_q \{R(q) - C(q)\}$$

This leads to:

$$R'(q^*(\theta)) = \theta,$$

which sets the social marginal revenue to social marginal cost. Additionally, $\frac{\partial q^*(\theta)}{\partial \theta} < 0$, through the Implicit Function Theorem and $R'' < 0$. This has a natural interpretation that in equilibrium the more efficient types will generate more sales. The level of transfers will be determined by the equilibrium sales and the participation constraint:

$$t^*(q, \theta) = t^*(\theta) = C(q^*(\theta)) + \bar{u} = \theta q^*(\theta) + F + \bar{u}.$$

All physician types produce at their efficient level, and the entire surplus from sales goes to the pharmaceutical companies.¹ Under the First Best there is no informational rent, as both parties have access to same information.

¹If there's bargaining between the physicians and the pharmaceutical companies, then the surplus would be divided between them.

Disclosure Laws

Each physician receives non-zero payoff, and it might not be profitable for the pharmaceutical company to employ all physicians, even at their optimal level of production. First, note that by the envelope theorem,

$$\frac{\partial (R(q^*(\theta)) - \theta q^*(\theta) - F - \bar{u})}{\partial \theta} = \frac{\partial (R(q) - \theta q - \bar{u})}{\partial \theta} \Big|_{q=q^*} = -q^*(\theta) < 0.$$

The total surplus decreases with less efficient types. Therefore, if $\exists \tilde{\theta}$ such that,

$$R(q^*(\tilde{\theta})) = \tilde{\theta} q^*(\tilde{\theta}) + \bar{u},$$

then,

$$R(q^*(\theta)) \leq \theta q^*(\theta) + \bar{u}, \quad \forall \theta \geq \tilde{\theta},$$

with the inequality being strict for $\theta > \tilde{\theta}$. Thus, $\tilde{\theta}$ is a cutoff value, and the pharmaceutical companies will only hire physicians who are more efficient than the cutoff value, $\theta < \tilde{\theta}$.

The effect of the disclosure laws can be treated as an increase in the outside option: the drawback of having payments revealed makes the physician's outside alternative more attractive. The reputational cost of accepting payments is passed onto the pharmaceutical company in terms of requiring higher payments to achieve the same effort. Effectively, the disclosure imposes a (constant) fixed cost of doing business with the drug manufacturer, which in the participation constraint is equivalent to an increase in the outside option. Under disclosure laws, the outside option for all types will become: $\bar{u} + \alpha$.

The higher outside option will not change the first order conditions, and the efficient level of production for a physician of type θ will still be $q^*(\theta)$. If the physician is employed by the pharmaceutical company, then the payment to the physician,

$$t(\theta) = \theta q^*(\theta) + F + \bar{u} + \alpha,$$

will increase. If there was a cutoff value to hiring physicians, $\tilde{\theta}$, then the higher outside option will lower the cutoff value:

$$\tilde{\theta}(\bar{u} + \alpha) < \tilde{\theta}(\bar{u}).$$

The region of physicians that are no longer paid, $[\tilde{\theta}(\bar{u} + \alpha), \tilde{\theta}(\bar{u})]$, denotes the least efficient types that were previously employed. The effect of the disclosure law is then two-fold: the payments (to the least efficient physicians) drop out, but the average payments to all other physicians increase.

Second Best

In the Second Best scenario, the pharmaceutical company observes an increase in sales – the sales quantity generated by the physician – but not the physician type. The payments then can only depend on quantity, q . Through the revelation mechanism, the set of optimal solutions can still be restricted to payoffs $\{(q(\theta), t(\theta))\}$, that are truthful in types:

$$(1) \quad t(\theta) - \theta q(\theta) \geq t(\theta_0) - \theta q(\theta_0), \quad \forall \theta_0 \in [\underline{\theta}, \bar{\theta}].$$

In the Second Best solution, the optimal solution also has to satisfy this Incentive Compatibility (IC) constraint. The IC constraint implies,

$$\frac{dq(\theta)}{d\theta} \leq 0.$$

Additionally, at the optimum, the payoff, $t(\theta)$, and equilibrium level of quantity, $q(\theta)$, will satisfy:

$$t'(\theta) - \theta q'(\theta) = 0.$$

The equilibrium Second Best quantity $q^{SB}(\theta)$, as a function of θ will be given by the following condition:

$$(2) \quad R'(q^{SB}(\theta)) = \theta + \frac{F(\theta)}{f(\theta)}.$$

If the distribution for θ satisfies the monotone hazard rate property:

$$\frac{d}{d\theta} \left(\frac{F(\theta)}{f(\theta)} \right) \geq 0,$$

then $q^{SB}(\theta)$ will satisfy the conditions necessary for the Second Best equilibrium.

The above solution has several implications. First, for the lowest type (i.e., most efficient) physician, $\theta = \underline{\theta}$, the First Best and the Second Best solutions will both satisfy the same condition:

$$R'(q^{SB}(\underline{\theta})) = \underline{\theta} = R'(q^*(\underline{\theta})).$$

Therefore the lowest type will produce at the same quantity as in the First Best outcome: there is no distortion for the most efficient type. However, for all the other types $\theta > \underline{\theta}$,

$$R'(q^{SB}(\theta)) > \theta = R'(q^*(\theta)),$$

meaning there will be downward distortion in the quantity produced, $q^{SB}(\theta) < q^*(\theta)$, for all the other types. The downward distortion stems from the information rent collected by less efficient types who no longer need to produce as much q for the same payment.²

The optimal transfer payment $t^{SB}(\theta)$ is given by:

$$t^{SB}(\theta) = \int_{\underline{\theta}}^{\bar{\theta}} q^{SB}(\tau) d\tau + \theta q^{SB}(\theta) + F + \bar{u}.$$

The above equation assumes all types of physicians receive some payments from the drug manufacturers. If the pharmaceutical companies would like to shut down some of the types, then they would maximize profits:

$$\max_{\{\underline{\theta}\}} \int_{\underline{\theta}}^{\bar{\theta}} \left(R(q^{SB}(\theta)) - \left(\theta + \frac{F(\theta)}{f(\theta)} \right) q^{SB}(\theta) - F - \bar{u} \right) f(\theta) d\theta,$$

giving the cutoff value of:

$$(3) \quad R(q^{SB}(\tilde{\theta})) = \left(\tilde{\theta} + \frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) q^{SB}(\tilde{\theta}) + F + \bar{u}.$$

The optimal payments can then be expressed as:

$$(4) \quad t^{SB}(\theta) = \int_{\underline{\theta}}^{\bar{\theta}} q^{SB}(\tau) d\tau + \theta q^{SB}(\theta) + F + \bar{u}.$$

It is again easy to check, that $\forall \theta \in [\tilde{\theta}, \bar{\theta}]$, $R(q^{SB}(\theta)) \leq \left(\theta + \frac{F(\theta)}{f(\theta)} \right) q^{SB}(\theta) + F + \bar{u}$.

Proof: Pick a θ . Then, by the Intermediate Value Theorem, and the fact that q is monotonic, $\exists \hat{\theta} \in [\tilde{\theta}, \theta]$, such that:

$$R(q^{SB}(\theta)) - R(q^{SB}(\tilde{\theta})) = R'(q^{SB}(\hat{\theta})) (q^{SB}(\theta) - q^{SB}(\tilde{\theta})).$$

Remember, that since, $q' \leq 0$, we have $q^{SB}(\theta) \leq q^{SB}(\tilde{\theta})$. Further,

² See Chen (2015) for an intuitive explanation of this mechanism in another legal application involving markets and the perceived legitimacy of experts (i.e., courts).

$$R' \left(q^{SB}(\hat{\theta}) \right) = \hat{\theta} + \frac{F(\hat{\theta})}{f(\hat{\theta})} > \tilde{\theta} + \frac{F(\tilde{\theta})}{f(\tilde{\theta})}.$$

Then,

$$R \left(q^{SB}(\theta) \right) - R \left(q^{SB}(\tilde{\theta}) \right) \leq \left(\tilde{\theta} + \frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) (q^{SB}(\theta) - q^{SB}(\tilde{\theta})),$$

or,

$$\begin{aligned} R \left(q^{SB}(\theta) \right) &\leq R \left(q^{SB}(\tilde{\theta}) \right) + \left(\tilde{\theta} + \frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) (q^{SB}(\theta) - q^{SB}(\tilde{\theta})) \\ R \left(q^{SB}(\theta) \right) &\leq \left(\tilde{\theta} + \frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) q^{SB}(\tilde{\theta}) + F + \bar{u} + \left(\tilde{\theta} + \frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) (q^{SB}(\theta) - q^{SB}(\tilde{\theta})) \\ R \left(q^{SB}(\theta) \right) &\leq \left(\tilde{\theta} + \frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) q^{SB}(\theta) + F + \bar{u} \\ R \left(q^{SB}(\theta) \right) &< \left(\theta + \frac{F(\theta)}{f(\theta)} \right) q^{SB}(\theta) + F + \bar{u}. \end{aligned}$$

Disclosure Laws under Second Best

Under the Second Best solution, the optimal transfer t is decreasing in θ . Otherwise, the IC constraint will be violated: if $\theta_1 < \theta_2$ and $t(\theta_1) \leq t(\theta_2)$, then

$$t(\theta_2) - \theta_1 q^{SB}(\theta_2) \geq t(\theta_1) - \theta_1 q^{SB}(\theta_2) > t(\theta_1) - \theta_1 q^{SB}(\theta_1),$$

which violates IC. Alternatively, from equation (3), we have that:

$$\frac{\partial t^{SB}(\theta)}{\partial \theta} = \frac{\partial q^{SB}(\theta)}{\partial \theta} \leq 0$$

The result is intuitive: the more efficient physicians produce more and are paid more.³ The effect of the disclosure laws can again be expressed as an increase in the outside option from $\bar{u}$ to $\bar{u} + \alpha$. The effect on Second Best payments will be twofold. First, the new cutoff threshold, $\tilde{\theta}(\bar{u} + \alpha)$, will decrease, relative to $\tilde{\theta}(\bar{u})$. The marginally effective physicians will drop out, as the surplus from their production will not be sufficient to cover the direct and indirect (outside option) costs of production.

³This result may not hold in the First Best scenario, since even the more efficient types produce more, they also produce at lower marginal cost. The overall cost, then could be higher or lower relative to more inefficient physicians. And since each doctor is paid according to their costs, the overall transfer may not reward more efficient physicians.

The effect on the payments for the remaining physicians is not obvious. The net difference in the transfers will be given by:

$$(5) \quad \Delta t^{SB} = \alpha - \int_{\tilde{\theta}(\bar{u}+\alpha)}^{\tilde{\theta}(\bar{u})} q^{SB}(\tau) d\tau,$$

which is composed of two effects. The effect of higher outside option will again raise the overall level of payments, given by the first expression, α . The more efficient types, however, also enjoy informational rents to incentivize them not to pretend to be inefficient. As the high types drop out, the amount of informational rents also decrease - this is the second effect.

To see the sign of the overall effect, it might be informative to evaluate the derivative:

$$\frac{\partial \Delta t^{SB}}{\partial \alpha} = 1 + q(\tilde{\theta}(\bar{u} + \alpha)) \frac{\partial \tilde{\theta}(\bar{u} + \alpha)}{\partial \alpha} = 1 + q(\tilde{\theta}(\bar{u} + \alpha)) \frac{\partial \tilde{\theta}(\bar{u} + \alpha)}{\partial (\bar{u} + \alpha)}$$

To evaluate the magnitude of the derivative, and more specifically the second term, it will be informative to look at the partial of equation (3) with respect to $\bar{u}$:

$$\begin{aligned} R'(q^{SB}) \frac{dq^{SB}(\tilde{\theta})}{d\tilde{\theta}} \tilde{\theta}'(\bar{u}) &= \left(1 + \frac{d}{d\tilde{\theta}} \left(\frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) \right) \tilde{\theta}'(\bar{u}) q^{SB} \\ &+ \left(\tilde{\theta} + \frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) \frac{dq^{SB}(\tilde{\theta})}{d\tilde{\theta}} \tilde{\theta}'(\bar{u}) + 1. \end{aligned}$$

Given the properties of $R'(q^{SB})$ from equation (2), this reduces to:

$$\left(1 + \frac{d}{d\tilde{\theta}} \left(\frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) \right) \tilde{\theta}'(\bar{u}) q^{SB} + 1 = 0$$

Since, $\frac{d}{d\tilde{\theta}} \left(\frac{F(\tilde{\theta})}{f(\tilde{\theta})} \right) \geq 0$ and $\tilde{\theta}'(\bar{u}) \leq 0$, we have:

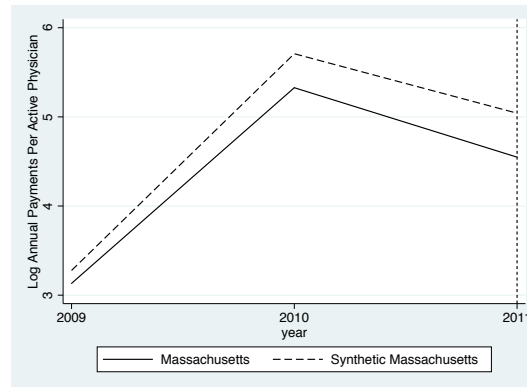
$$\frac{\partial \Delta t^{SB}}{\partial \alpha} 1 + q(\tilde{\theta}(\bar{u} + \alpha)) \frac{\partial \tilde{\theta}(\bar{u} + \alpha)}{\partial (\bar{u} + \alpha)} > 0$$

Thus, the slope of the variable of interest is positive. And when $\alpha = 0$, $\Delta t^{SB} = 0$, for a positive increase in α , the transfers increase. Therefore, the effect of disclosure laws is twofold. First, mandatory disclosure increases the average payoff to the paid physicians, because for a given physician effort, the payment to physician increases. Second, the marginally effective physicians drop out and we should observe a drop in small payments.

APPENDIX 11: SYNTHETIC CONTROL

We also employ synthetic control and report that the point estimate is 0.287, which is near the original estimate of 0.356. We present the deviation from trend using only three data points for each group of states in the attached response. We use the statewide demographics (the same ones as in Table 3—household income, average physician wage, cost of living, % population < 18 , % population ≥ 65 , % unemployment, % $\geq$ high school education, % health insurance, annual prescription drugs filled at pharmacies/person, population density, number of active physicians, and number of active nurses) in the pre-treatment period to construct the weights. The weights selected by synthetic control and corresponding time-series graph are presented below.

Weights	State
0.291	New Hampshire
0.234	Pennsylvania
0.217	New York
0.101	District of Columbia
0.088	Maryland
0.067	Vermont
0.002	Rhode Island



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