Drug Diffusion through Peer Networks: The Influence of Industry Payments

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Abstract

Peer effects may amplify the decisions of early technology adopters as information spreads through local networks. Drug detailing efforts of pharmaceutical companies may leverage peer influence within existing provider networks to broaden their reach beyond the directly targeted physicians. Using matched physician data from Medicare Part D and Open Payments, we investigate the influence of pharmaceutical payments on the prescription of new anticoagulant drugs. First, we show that pharmaceutical payments target physicians who share patients with many different providers and thus may influence a broader network of peers. Within a difference in differences framework, we find a physician's own prescription of new anticoagulant drugs increases following a pharmaceutical payment, relative to the physician-specific baseline prescribing rate for that drug. The effect scales with the size of the payment, with larger payments spurring larger increases in prescribing. Peers of targeted physicians also increase their prescribing of the new drug after the targeted physician receives a large payment. To estimate the scale of peer effects in prescription decisions, we use peer payments as an instrumental variable for peer prescription volume. We find that when doctor's peers increase their use of a new drug by 1 beneficiary per quarter, the doctor's own use rises by 0.3 beneficiaries per quarter. Results suggest that spillover effects on peers are an important channel through which payments influence prescriptions.

Keywords: healthcare, innovation diffusion, peer effects, networks, pharmaceutical detailing

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1 Introduction

As medical technology advances and standards of care evolve, physicians must continually assimilate new information about treatment options. Prior research has found wide variation in the adoption of new health technologies across regions and significant local clustering of treatment patterns. (Abaluck et al., 2014; Cutler et al., 2013; Skinner and Staiger, 2015; Moen et al., 2016; MacLeod and Currie, 2018). A possible explanation for clustering of care practices is that physicians may learn about new technologies from their peers, so regional adoption levels will depend on the seeding and structure of local physician networks.

The importance of peer influence in technology adoption has been documented, e.g., in Oster and Thornton (2012).[1] In medicine, learning from peers may be particularly important, because each physician treats a relatively small and heterogeneous set of patients, and mistakes are costly. However, research into peer effects faces a significant hurdle, which is that local clustering may be the result of common shocks or correlated preferences, and not the direct result of peer effects. Research on peer effects in other contexts has exploited randomized experiments, structural modeling of peer networks, and natural experiments to isolate peer effects from these competing explanations. In this paper, we exploit quasi-random variation in promotional payments and in-kind transfers physicians receive from pharmaceutical companies to estimate peer effects in prescription behavior.

Pharmaceutical companies' drug detailing efforts are thought to comprise an important source of local information about new drugs and may help shape local patterns of drug diffusion. Recent evidence suggests these efforts influence physicians, and an ongoing public debate centers on the influence of drug manufacturers' promotional efforts (Sinkinson and Starc, 2015), and particularly payments to physicians (e.g., Campbell et al., 2007; Navathe and David, 2009; David et al., 2010; DeJong et al., 2016). However, most of the related research does not consider peer effects, which could amplify the influence of these payments. Indeed, pharmaceutical companies reportedly target "thought leaders".[2] This study's contribution is therefore twofold: it provides both a lens for understanding the role of information

[1] Peer effects have also been documented in many other domains, e.g., Calvó-Armengol et al. (2009); Carrell et al. (2009); Bayer et al. (2009); De Giorgi et al. (2010); Kuhn et al. (2011)

[2] Elliot, Carl, "The Drug Pushers," *The Atlantic*, April 2016.

diffusion through local networks and a more complete accounting of the impact of pharmaceutical companies' promotional efforts through spillovers.

To study prescription behavior, we use Medicare Part D administrative claims data. We focus on prescriptions of anticoagulants (commonly referred to as "blood thinners"), a widely utilized therapeutic class to which several new drugs were introduced during or shortly before our sample period. We match prescriptions data with two other sources of data: (i) the universe of payments and value transfers to US physicians by drug manufacturers and distributors, and (ii) data on physician networks of shared patient relationships. Combined, these data provide a unique opportunity to study spillovers in prescription behavior and the effects of industry payments, for two reasons. First, because shared-patient relationships are non-transitive, we observe differences in the reference group even among connected physicians. Second, the longitudinal nature of the data allows us to study the response of prescription to seeding of information that is associated with pharmaceutical payments at different points in time.

Analyzing this novel matched database, we confirm earlier findings showing that payments and prescriptions are correlated. Furthermore, we show that while nearly all practicing physicians receive small payments associated with detailing visits by marketing salespersons, relatively few, more specialized physicians, receive large payments that are associated with speaking, consulting, and other services. Nonetheless, large payments constitute a large fraction of all payments and account for most of their total dollar volume. Furthermore, large payments are often made to physicians with large number of peers.

To identify peer effects separately from unobserved factors that may be correlated across referring physicians, such as correlated physician tastes or patient demand, we exploit variation in both the timing of payments to physicians and their peer group composition. Our empirical strategy consists of two complementary approaches. First, using a difference-in-differences framework, we estimate the impact of payments made to a physician group of peers on her own prescription behavior. Second, using payments as an instrument for peer prescriptions, we estimate peer-effects in prescription behavior. The first approach highlights the spillover effects payments to physicians may have through their indirect influence on the payment recipients' peers. The second approach highlights and quantifies one potential

mechanism for such influence, namely, peer effects in prescription behavior.

Receiving a payment is associated with a stable increase in prescription volume, with larger effect sizes tracking larger payment sizes. Difference-in-differences estimates of the effects of payments suggest that small payments of up to $30 lead to 0.04 additional prescribed beneficiaries per quarter in our sample. Payments greater than $30 lead to 0.14 additional prescribed beneficiaries per quarter. Payments greater than $300 are lead to 0.50 additional prescribed beneficiaries. Naive estimates that do not include physician fixed effects and time trends are biased upwards by 25% to 200%.

Having a peer paid more than $300 is associated with a modest but significant increase in own prescription volume of 0.01 additional beneficiaries per quarter. This effect of a large peer payment is 1/3 the estimated effect size of any own payment, and 1/36 the size of an own payment of the same magnitude. These results suggest the impact of a payment decays as it ripples through the physician network. However, given that the physicians targeted with these large payments have 62 peers on average, a back of the envelope calculation scales the total effect of a $300 payment across all first-degree peers at $0.014 * 62 = 0.87$ additional beneficiaries per quarter. This estimated impact of a large payment on all first-degree peers eclipses the estimated impact of a large payment on the paid physician's own patient volume.

Instrumental variable estimates further show that peer effects in prescription contribute substantially to the spillover effects of pharmaceutical payment. If a doctor's peers' prescription volume for a new anticoagulant increases by 1 beneficiary per quarter on average, we predict that the doctor's own prescription volume will increase by 0.27 prescriptions per quarter.

Our results imply that the impact of pharmaceutical payments on the adoption of new drugs is greatly amplified through peer effects. Back-of-the-envelope calculations based on our estimates suggest that the magnitude of indirect spillovers account is on the same order as their direct effect. This implies that drug manufacturers and distributors have a greater ability to influence medical practice than one would have estimated neglecting peer effects, though in the absence of a benchmark for the appropriate prescription behavior of these new drugs, this can have either a positive or a negative effect on welfare. More generally, our results suggest that in cases with under-adoption of useful technologies, exploiting available

information on the structure of interaction between physicians to target interventions can expedite the diffusion of beneficial technologies. Our results also suggest that peer effects should be acknowledged when considering the nature of competition in the markets for new medical technologies and in the marketing strategies associated with promoting such products.

2 Data

To estimate peer effects in the diffusion of new drugs, we combine multiple databases on prescription, payments, and connections as follows: physician prescription volumes are obtained from Medicare Part D administrative claims; associated payments and in kind transfers to physicians made by drug manufacturers are obtained from the Open Payments database; Physician shared-patients relationships are obtained from the Referral Patterns database; additional physician characteristics are obtained from Physician Compare database.[3]

2.1 Data Sources

Prescriptions We analyze a 40% sample of Research Identifiable Medicare Part D claims in 2014–2015 (CMS, 2013–2015). We focus on one class of drugs, anticoagulants (commonly referred to as "blood thinners"). During the sample period, four new anticoagulant agents, known as the new oral anticoagulant drugs (NOACs), were approved by the FDA and covered by Medicare Part D: apixaban (brand name Eliquis), dabigatran (Pradaxa), edoxaban (Savaysa), and rivaroxaban (Xarelto). We choose to focus on NOAC, because they were introduced just before or during our sample period. Therefore, we observe them gain market share and replace exiting treatment options, primarily coumadin (Warfarin), an anticoagulant that was originally approved in 1954 and has been off-patent for decades (Figure 1).[4]

[3]With the exception of the Medicare Part D Research Identifiable patient-level data, all data are publicly available. All of these databases are maintained by the Centers of Medicare and Medicaid Services (CMS), a federal agency within the US Department of Health and Human Services.

[4]The FDA first approved Pradaxa on Oct 19, 2010; Xarelto on Jul 1, 2011; Eliquis on Dec 28, 2012; Savaysa on Jan 8, 2015. Cited advantages of NOACs relative to previously existing anticoagulant drugs include improved safety, convenience of use, a wider therapeutic window, and no need for laboratory monitoring (Mekaj et al., 2015).

The diffusion of these new drugs forms the basis of our analysis.

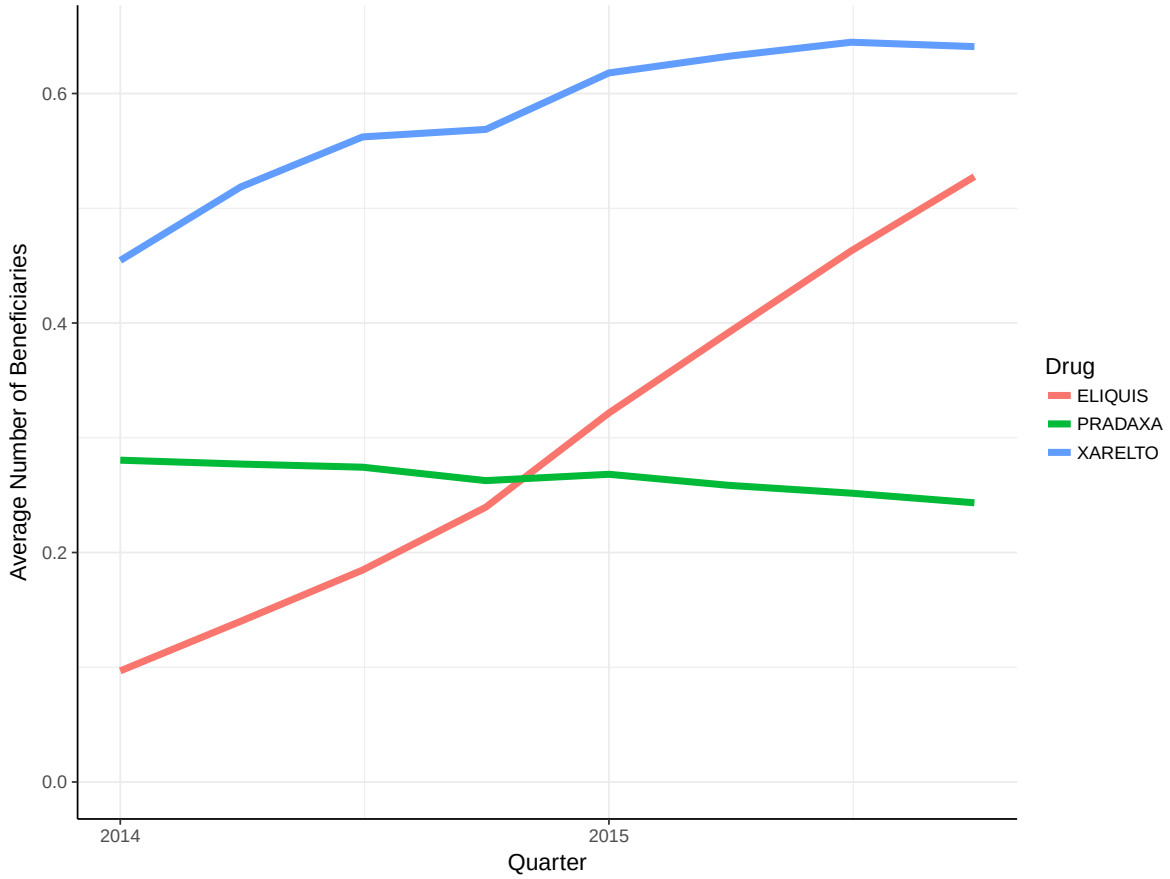
To track the adoption and use of new anticoagulant drugs, we restrict attention to physicians of medical specialties that together include the majority of NOAC prescribers: primary care and cardiology.[5] For each physician of these specialties and each anticoagulant drug, we construct quarterly panel of the number of unique Medicare Part D beneficiaries prescribed the drug.

Peers To study peer effects in prescription decisions, we combine prescription information with physician referral data from CMS Referral Patterns data (CMS, 2013b). In these data, two physicians are said to have a *shared patient* if one participated in the delivery of health services to the same patient within a 30 days period after another physician. Two physicians are defined to be *peers* if they have 11 or more shared patients within a year.[6] Survey analysis has validated that physicians with multiple shared patients are in most cases familiar with each other (Barnett et al., 2011), suggesting peers thus defined may also influence each other's practice. One channel for such potential influence in prescription behavior is via observing peer prescription behavior for shared patients. To reduce endogeneity concerns, we define peers based on the observed network of shared-patient peers in 2013, the baseline year of our sample. Table A1 presents summary statistics on the distribution of the number of peers. The mean physician in our sample share patients with 22.8 peers (median 13). Cardiac specialists, whose practice is more specialized, have significantly more peers (mean 60.2, median 53) than generalists (mean 17.1, median 11). So do more experienced physicians. For simplicity, we treat this network as static, undirected, and unweighted. These simplifications can be relaxed.

[5]We define as primary care specialist the physicians whose primary specialty recorded in Physician Compare database, described below, is one of: Family Practice, Internal Medicine, General Practice, and Geriatric Medicine. Cardiologists are defined as physicians whose primary specialty is one of: Cardiology, Interventional Cardiology, and Cardiac Surgery.

[6]Physicians i, j share a *common patient* if there exists a patient who had encountered i and j within a 30-day time interval. Let n_{ijt} denote the number of unique common patients i and j had during a year t. We record a link between i and j, namely, consider them as peers in t, if $n_{ijt} > 10$ in year t. Note that for privacy reasons we observe n truncated to 0 for $n_{ijt} \leq 10$. Therefore, providers with no links are ones that have no other providers with whom they share 11 or more patients within the year.

Figure 1: Prescription Volumes over Time



Notes: For the three NOACs we study, the figure shows the prescribed beneficiaries per quarter in our sample. The FDA first approved Pradaxa in 2010; Xarelto in 2011; Eliquis in 2012. Source: authors' calculations based on 2014–2015 Medicare Part D data.

Payments We combine data on NOAC drug prescriptions with data on associated payments and value transfers to physicians by drug manufacturers and distributors in the period Q32013–Q42015 from the Open Payments database (CMS, 2014–2015). This database is maintained by CMS as part of the Physician Financial Transparency Reports (Sunshine Act), a national disclosure program created by the Affordable Care Act (ACA). Beginning in 2013, manufacturers are required to submit data about all payments and other transfers of value made to physicians (which we henceforth refer to as *payments*). The reports include the amount paid, the associated drug(s), and the nature of payment or transfer of value. Appendix Figure A1 shows, for all payments associated with NOAC drugs, the distribution of payment size by payment type. The largest number of payments are for food and beverages paid for by detailing salespeople cover when discussing new drugs with physicians (Figure 3). These small payments are received by both generalists and specialists. In contrast, the largest category of payments by dollar volume is compensation for services such as speaking fees. These large payments are distributed to a small fraction of physicians, most of whom are specialists (Figure 4 shows average payments associated with each drug, by physician specialty; Figure A3 shows similar figures, but instead of averages, it shows the fraction of physicians paid above \$0, \$30, and \$300).

Linkage Although Open Payments data and Medicare Part D are both maintained by CMS, they do not share a unique identifier. While in Part D data physicians are identified by their National Provider Identifier (NPI) number, in Open Payments data physicians are only identified by their full name, specialty and practice address. We therefore use name and location data to match these records. Specifically, we match the name and address reported in Open Payments to the entire history of addresses reported to CMS which we obtain from Physician Compare, a public directory with information on all physicians and other health care professionals who provide Medicare services (CMS, 2013a). We were able to match 85% of all paid physicians—more than 90% of the estimated fraction of 93% of physicians that accept Medicare patients according to surveys.[7]

[7] "Primary Care Physicians Accepting Medicare: A Snapshot, The Kaiser Family Foundation", Accessed May 2018, https://www.kff.org/medicare/issue-brief/primary-care-physicians-accepting-medicare-a-snapshot/.

2.2 Patterns of Pharmaceutical Payments, Prescriptions, and Number of Peers

There is a positive correlation both between payments to physicians and their number of direct peers and between payments and prescription volume. Table 3 shows summary statistics by physician own and peer payment status. Physicians with higher payment associated with a drug are more likely to prescribe the drug. Recipients of higher payments have on average more peers. Specialty is also a strong determinant of payments: while cardiologists constitute a small share of the overall physician population, they are the majority (76%) of recipients of payments exceeding $300. These large, less common payments are the main source of identifying variation in our design.

3 Identification and Estimation

The focus of our analysis is estimating peer effects in physician prescription behavior and its contribution to spillovers effects of pharmaceutical payments on prescription. The main concern is endogeneity in peer prescriptions. To address it, we take two complementary approaches: a difference-in-differences approach around the timing of payments, and instrumenting for peer prescriptions by peer payments. Both approaches exploit variation in the timing of payments and differences between physicians in the composition of their reference group of peers.

We model prescription decisions as a function of physician's peers' prescriptions, and of the payments both physicians and their peers receive over time. Let $i = 1, \ldots, N$ index physician providers, $t = 1, \ldots, T$ index time in quarters, and $d \in D$ index drugs. Let Y_{itd} denote the volume prescriptions of drug d made by i at period t, and let P_{itd} denote the sum of payments associated with drug d made to i in quarter t. Let G denote the network of relationships among providers based on having common patients (see Section 2 for definitions). That is, for each i, j, let $s_{ij} = 1$ if i and j shared patients and zero otherwise. With slight abuse of notation, let Gi denote the group of direct peers of i in the network G.[8] Because peer relationships are non-transitive, $j \in G_i$ does not imply $G_j = G_i$. Namely,

[8]We model the network as undirected and unweighted. Our model can easily be extended to incorporate

peer groups vary even between connected peers.

To find the causal impact of payments and peer prescription on a physicians' own prescription volume, one would ideally observe a random assignment of peers, peer prescription behavior, and payments. In such case one could estimate the following linear-in-means model even with cross sectional data:

$$Y_i = \alpha_i + \beta Y_{Gi} + \gamma P_i + \varepsilon_i. \tag{1}$$

where Y is the outcome of i and Y_{Gi} is the mean outcome among i's peers. However, estimates from this model with non-experimental data such model could be biased because prescription choices may be correlated among peers due to unobserved factors. Examples for such potential factors are similarity in taste and correlated patient demand among physicians who practice together.

Absent experimental variation in peer assignment, payments, and prescription behavior, we take two alternative approaches. The first is a difference in differences approach, comparing prescription volumes before and after the first payment made to each physician and/or to this physician's peers. We estimate the model:

$$Y_{itd} = \alpha_{id} + \beta_{dts} + X'_{idt}\gamma + \sum_k \delta_{k(i,d,t)} + \sum_l \eta_{l(Gi,d,t)} + \varepsilon_{idt}, \tag{2}$$

where i index doctors, t index time, s index medical specialties (PCP or specialist), and d index drugs. The terms α and β are doctor×drug and drug×quarter×specialty fixed-effects, and X_{idt} includes differential time trends for those with any payments during the sampled period; the coefficients $\delta_{k(i,d,t)}$ and $\eta_{l(Gi,d,t)}$ denote event-time dummies for the number of periods k since physician i first received payment associated with drug d and for the number of periods l since the first such payment was made to any direct peer of i in the network G. These event-time coefficients are the main parameter of interest, capturing the response of prescription behavior to prescription made to a physician and her peers. Because a fully flexible dynamic specification that includes pre- and post-event period fixed effects *and*

weights or directed links.

linear time trends is underidentified we follow the strategy described in Borusyak and Jaravel (2016) and first test for pre-trends in prescription prior to payment events (using F-test of the coefficients with $k < 0, l < 0$ being different than zero), before dropping pre-period dummies from subsequent regressions. Our analysis finds no significant pre-trends. To flexibly capture the differential effect of payments of a different nature (e.g., small payments for food and beverage to large speaking and consulting fees), we use separate event-time counts and time-trends for different payment sizes. The model allows for drug-specific trends, pooling all drugs together. For clarity of notation, we henceforth omit the index d when it appears on all terms.

The second approach uses payments to instrument for peer prescriptions. The first and second stages are:

$$Y_{Gi,t-1} = \tilde{\eta} P_{Gi,t-2} + \tilde{\delta} P_{i,t-1} + X'_{it}\tilde{\gamma} + u_{it} \tag{3a}$$

$$Y_{it} = \theta \widehat{Y}_{Gi,t-1} + \delta P_{i,t-1} + X'_{it}\gamma + \alpha_i + \beta_{ts} + v_{it} \tag{3b}$$

Where $Y_{Gi,t}$ is the mean prescriptions of each drug by i's peers at t, and $P_{Gi,t}$ is the cumulative sum of the number of payments above the threshold made to peers in each quarter (by design, the same peer is counted multiple times if paid in multiple quarters). X_{it} includes differential time trends for having any peer paid above \$300 and, separately, for being ever paid above each of \$0, \$30, and \$300. Using lagged payments as instruments for peer prescriptions only assumes weak exogeneity assumption, i.e., that past peer payments are uncorrelated with unobservables affecting current prescriptions ($E[v_{it}P_{Gi,t-2}] = 0$).

We use the generalized method of moments to estimate this model.

Discussion These approaches address several threats to identification of peer effects that arise with data on groups (Manski, 1993) or with cross sectional, rather than longitudinal data on networks (Bramoullé et al., 2009). The problem with groups (e.g., all physicians affiliated with a hospital), is that being in the same group is mostly a transitive relation, and therefore there is little variation in the reference groups of similar agents.[9] In contrast,

[9]Unless groups partially overlap, see De Giorgi et al. (2010)

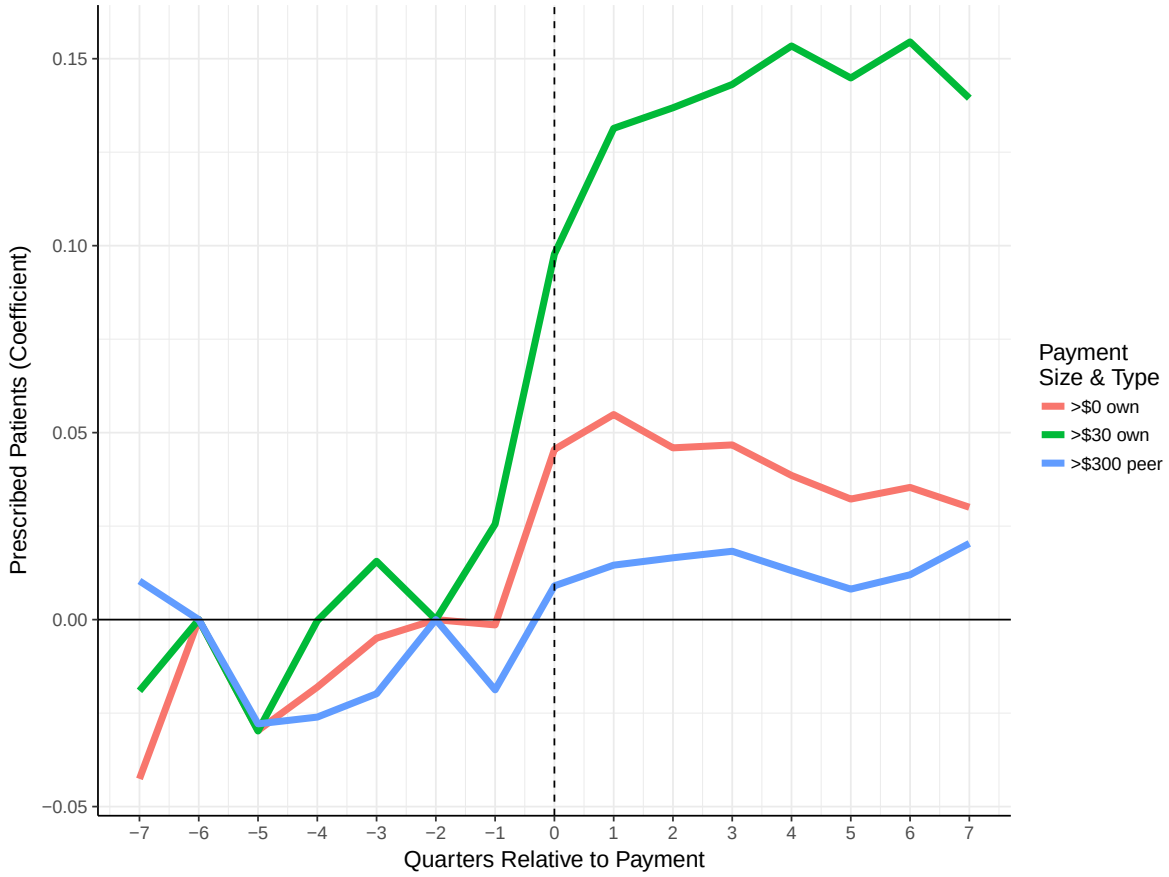
physician shared-patient networks are intransitive (the global clustering coefficient is 0.37, meaning only a third of connected triples are fully connected), and so even similar physician often interact with different sets of peers. Longitudinal data contribute variation in the timing of payments. Our strategy uses these variations in both payment timing and network structure. It accounts for the possibility that payments target high prescribers, and for the possibility that payments are associated with unobserved time invariant physicians characteristics.

The two approaches complement each other as they estimate two closely related, but separate effects. The first, difference in differences approach estimates the impact of payments to a physician on peer prescription behavior. this affect could arise due to multiple different channels. Recipients of payment, especially of large payments, may proselytize the use of the associated drug. Alternatively, recipients of payments may prescribe more of the associated drug, and observing this increased use by following shared patients, peers may also decide to prescribe more of the same drug. The importance of this second channel—peer effects in prescription behavior—is specifically quantified by our second, IV approach. Furthermore, our IV estimates of peer effects in prescription are also of interest because peer influence in medical technology adoption may occur for many reasons unrelated to drug detailing, and these estimates help us understand the magnitude of such spillovers.

4 Results

We begin by estimating equation 2 to explore the relationship between peer payment and prescription volume. First, we consider a series of graphs to explore visually and test statistically for stability of pre-trends prior to first payment. These graphs plot the event-time coefficients from a regression where the outcome is quarterly prescription volume, calculated at the physician level. Quarter 0 indicates the quarter of payment. Quarters -6 and -2 are excluded from the set of event time dummies to identify pre-trends.

Figure 2: Event Study



Notes: Event study coefficients estimated from equation 2, showing the response of physicians to own and peer payments of different sizes. Each payment shock is modeled as having an independent and additive impact on prescription volume, hence the post-period dummies reflect the impact of a single payment shock. Quarter 0 indicates the quarter of payment. Quarters -6 and -2 are excluded from the set of event time dummies to identify pre-trends. Coefficients of own payments > 300 included but not shown, because their magnitude shadows that of all other effects (see Appendix Figure A2)

Figure 2 illustrates that after controlling for linear differential time trends, prescription volume remains stable prior to the first payment exposure. An F-test fails to reject the joint significance of the pre-period quarter indicator variables for own payments greater than $30, own payments greater than $300, and peer payments greater than $300 at the 5% level. Notably, the F-test does reject the joint significance of the pre-period quarter indicator variables for receiving any positive payment at the 1% level. Despite their statistical significance, the graph reveals that any pre-period deviations from trend are economically small in magnitude, and much smaller than the subsequent estimated impact of payments in the post-period.

Following initial payment, we see an increase in prescription volume. The graphs reveal the increase to be remarkably stable and persistent over the study window of up to 7 quarters following initial payment. Because each payment shock is modeled as having an independent and additive impact on prescription volume, the post-period dummies reflect the impact of a single payment shock.

Table 1: Results: The Impact of Payments on Prescriptions

	Dep. Var: Own prescription				
	Controls		By Drug		
	Minimal	Full	Xarelto	Eliquis	Pradaxa
Cumulative number of quarters:					
paid>$0	0.095	0.042	0.021	0.089	-0.008
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
paid>$30	0.180	0.141	0.050	0.273	0.019
	(0.007)	(0.005)	(0.005)	(0.010)	(0.013)
paid>$300	0.761	0.500	0.193	1.033	0.119
	(0.054)	(0.051)	(0.060)	(0.115)	(0.061)
peers paid>$300	0.041	0.014	0.004	0.026	0.000
	(0.002)	(0.002)	(0.004)	(0.005)	(0.003)
Doctor*Drug Fixed Effects	No	Yes	Yes	Yes	Yes
Differential trend by payment group	No	Yes	Yes	Yes	Yes
Drug*Specialty*Quarter fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Estimates of equation 2 for all drugs combined with different controls and for each drug separately with full controls

Receiving a payment is associated with an increase in prescription volume, with larger effect sizes tracking larger payment sizes. Summary measures of payment effects are reported in Table 1. These results are from direct estimates of equation 2, excluding any indicator variables for pre-payment quarters. Payment effects are calculated as the weighted average of the treatment effect in each of 7 post-period quarters, with weights corresponding to the size of the sample identifying each quarter. Accordingly, quarters immediately following the payment receive more weight than later quarters.

Small payments of less than $30 lead to 0.04 additional prescribed beneficiaries per quarter in our sample. Payments greater than $30 lead to 0.14 additional prescribed beneficiaries per quarter. Payments greater than $300 lead to 0.50 additional prescribed beneficiaries.

Having a peer paid more than $300 is associated with a modest increase in own prescription volume of 0.01 additional beneficiaries per quarter. This effect of a large peer payment is 1/3 the estimated effect size of any own payment, and 1/36 the size of an own payment of the same magnitude. These results suggest the impact of a payment decays as it ripples through the physician network. However, given that the physicians targeted with these large payments have 62 peers on average, a back of the envelope calculation scales the total effect of a $300 payment across all first-degree peers at $0.014 * 62 = 0.87$ additional beneficiaries per quarter. This estimated impact of a large payment on all first-degree peers eclipses the estimated impact of a large payment on the paid physician's own patient volume.

These results can be compared to a naive estimate of payment impacts, that does not control for provider-drug fixed effects or differential trends by payment group. Results of the naive regression are biased upwards, suggesting effect sizes that are 25% to 200% greater than estimates in the controlled regression.

4.1 Instrumental Variables Estimates of Peer Effects

There are two mechanisms by which having a peer targeted with a pharmaceutical payment may raise a doctor's prescribing, holding constant any own payments received. First, the physician network we study is linked through shared patients. When a patient sees two different physicians within a short time window, each physician has an opportunity to learn about the other physician's practice patterns. Seeing a colleague prescribe a new drug may

provide a positive signal about the value and applications of the new product, increasing the odds that a doctor adopts the new drug and prescribes it himself.

Part of this peer effect may be driven by prescription refills, for example when a primary care physician orders a refill of a prescription that was initiated by a cardiologist. As the doctor becomes more familiar with the new drug, he may also choose to initiate new prescriptions with the drug. In planned analysis, we will exclude prescription refills by restricting our sample to patients who have no prior prescription for anticoagulants.

The second mechanism by which a paid physician may influence his peers is through direct "proselytizing" about the new drug. Based on our conversations with physicians and consultants with expertise in drug detailing, we hypothesize that this mechanism is less important, particularly given the social and institutional distance between most physicians who share patients. In planned analysis, we will explore this possibility by testing whether the estimated peer effects exert a stronger influence among physicians who practice at the same location, holding fixed the volume of shared patients between two doctors.

In this section, we focus on the first learning mechanism and estimate the impact of an increase in peers' prescription volume for a new drug on a doctor's own prescription volume. In this specification, the pharmaceutical detailing payment to a physician's peers is an instrumental variable for peer prescribing volume. We then trace out the influence of peer prescriptions on own prescribing.

If we assume there is no proselytizing, then these instrumental variable estimates of peer effects may generalize to settings where peer prescription decisions are not driven by pharmaceutical payments. In the presence of a proselytizing channel, they provide an upper bound on the magnitude of peer effects we would expect in settings where an increase in peer prescription volume for a new drug is not accompanied by proselytizing that may be specifically inspired or motivated by the pharmaceutical payment.

Let's call the focal physician Doctor A, and the focal time period t. We are interested in how prescribing by the peers of Doctor A influence Doctor A's own prescription volume. We will use large pharmaceutical detailing payments received by the peers themselves as an instrument for the average peer prescription volume.

The first stage regression will predict the average prescription volume across all of Doctor

A's direct peers in period $t-1$. The instrumental variable is defined as the cumulative count of payments to Doctor A's peers that exceed \$300, through period $t-2$.

The second stage regression predicts Doctor A's own prescription volume in time t and the endogenous regressor is Doctor A's peers' average prescription volume in time $t-1$. Using peer payments as an instrumental variable for peer prescription volume helps us separate correlations between Doctor A's prescriptions and his peers' prescriptions that may be driven by common shocks. The instrumental variable specification controls for the impact of Doctor A's own payments through a dummy variable for receiving any positive payment (as of $t-1$) and a control for the natural log of cumulative own payments (as of $t-1$).

The instrumental variable analysis continues to exploit the panel structure of our data to isolate deviations from a doctor's baseline use of a new drug that occur shortly after a new peer payment shock. As before, we control for differential trends in prescription volume for physicians that may differ depending on whether the physician had a paid peer, and whether the physician himself received a small ($>$ \$0), medium ($>$ \$30), or large payment ($>$ \$300). We also continue to control for physician-drug fixed effects, and quarter-drug-specialty fixed effects.

Table 2: Results: Peer Effects in Prescription Behavior

	Dep. Var: Own prescription			
	1st Stage		IV	
	Coeff	Std. Err.	Coeff	Std. Err.
Total peer-quarters paid (t-2)	0.015	0.001		
Mean peer prescription (t-1)			0.275	0.056
Any own payment (t-1)	-0.118	0.002	-0.206	0.009
Log(sum own payments t-1)	0.035	0.001	0.072	0.003
Trend: any peer above 300	0.047	0.001	-0.005	0.003
Trend: any pay above 0	0.004	0.000	0.004	0.001
Trend: any pay above 30	0.003	0.001	0.014	0.001
Trend: any pay above 300	-0.014	0.002	0.131	0.003

Notes: Generalized method of moments estimates of the instrumental variable model in equations 3a and 3b.

In the first stage regression, we estimate that an additional payment to a doctor's peers of over $300 raises the average quarterly peer prescription volume by 0.015 beneficiaries per quarter (statistically significant at the 1% level; Table 2). Note that this effect is much smaller than the estimated impact of a large payment on the targeted doctor himself, but this reflects the fact that we are averaging prescriptions across all doctors' peers, only one of whom was hit with the payment shock. This averaged impact will reflect a combination of the direct impact of a large payment on the targeted physician, as well as any ripple effects due to peer linkages between the paid physicians' peers and other peers of Doctor A.

The second stage regression finds that if a doctor's peers' prescription volume for a new anticoagulant drug increases by 1 beneficiary per quarter on average, we predict that the doctor's own prescription volume will increase by 0.27 prescriptions per quarter. The result suggests that physician peer effects may play an important role in the diffusion of new drugs.

5 Conclusion

This study estimated the spillover effects of pharmaceutical payments and the part of such spillovers working through peer effects in prescriptions of new anticoagulant drugs. We used rich administrative data on physician prescriptions, the universe of payments to physicians from pharmaceutical companies, and networks of patient sharing. The strategy exploits variation in both the timing of payments and differences between physician in the reference group of peers. We use difference in differences to evaluate the response of prescription behavior to both own and peer payments. We also estimate peer effects in prescription—a potential channel for spillovers effects of payments—by instrumenting for peer prescription using peer payments.

Event study results show a significant and persistent increase in prescription of new drugs following the receipt of payments associated with these drugs, with larger payment having a greater effect on prescriptions. Remarkably, payments not only affect prescription made by their direct recipients, but also have spillover effects—they lead to increased prescriptions by recipients' peers. Summed over all peers, spillover effects are as important, if not more important, than direct effects of payments. Our peer effects estimates suggest that learning

from peers is an important channel through which payment spillover occur, and perhaps also an important channel for adoption of new technologies in medicine more generally.

We acknowledge several limitations to this study. More can be done to unpack the channels through which peer effects occur. For example, our current results do not distinguish between diffusion of new drugs that are the result of one physician's refilling prescriptions initially made by others, and diffusion that occurs through higher-level learning of drug properties. Another open question is why drug manufacturers provide both small and large payments, and whether there is any interaction between the effects of both types of payments on prescriptions. Finally, the welfare impact of spillover effects in payments are unclear, if the relative value of the adopted and existing treatments are not clearly ranked. These and other directions are left for future work.

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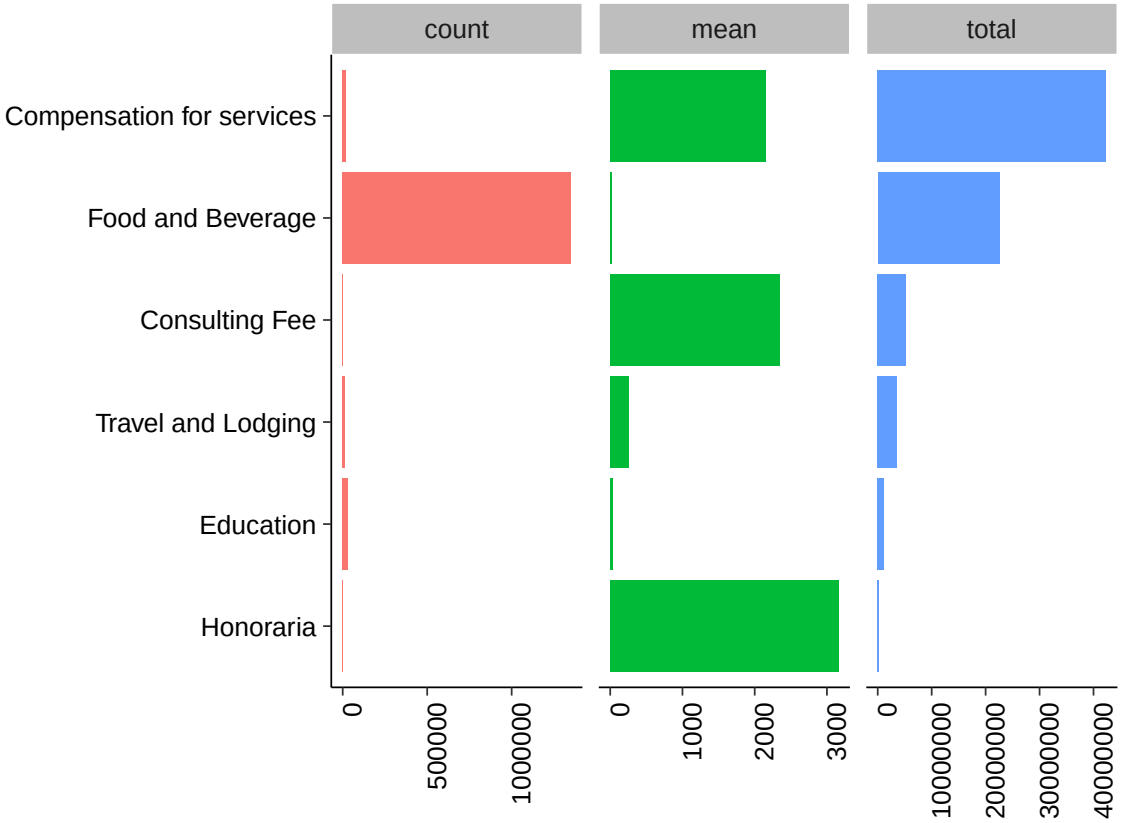
Tables and Figures

Table 3: Summary Statistics by Payment Status

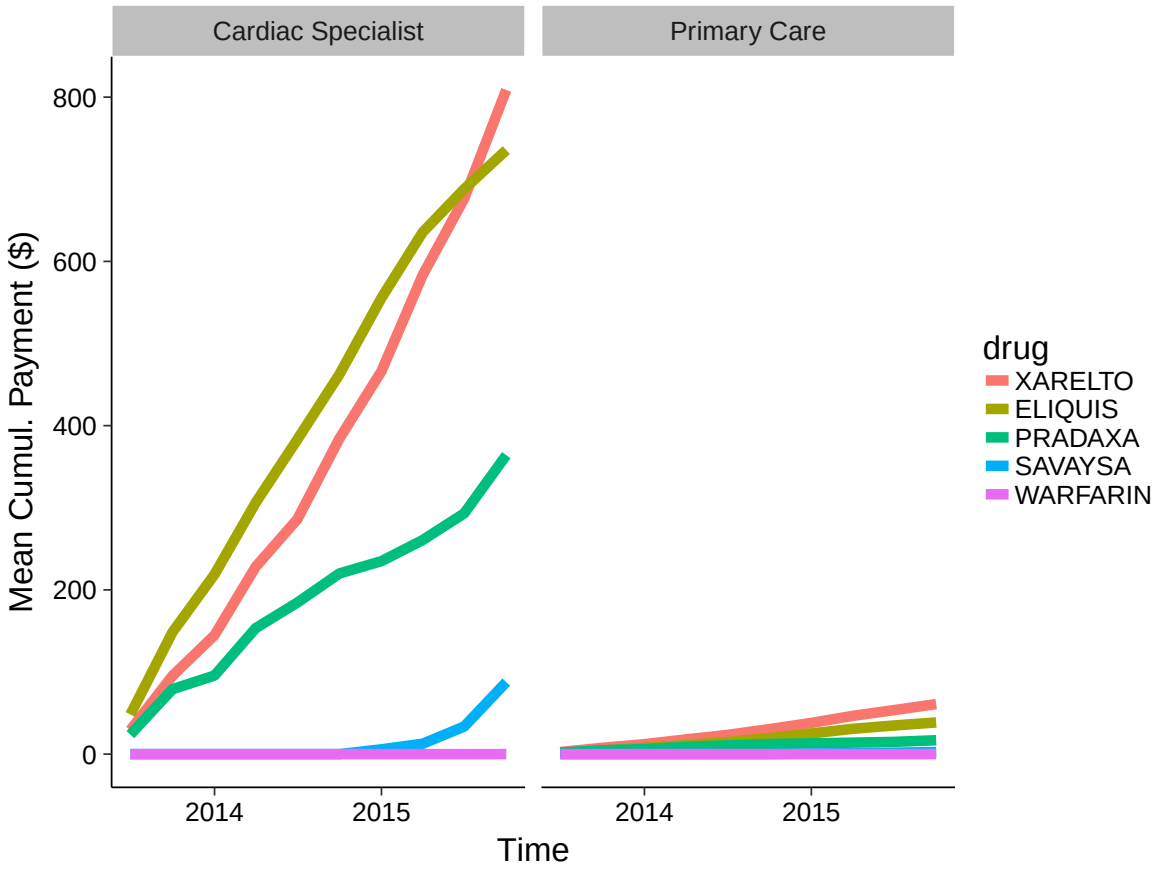
	Own Payments				Peer Payment
Summary Statistics	No payment	Any pay >0	Any pay >30	Any pay >300	Peer pay >300
Number of prescribed patients per quarter	0.39	0.61	1.40	5.07	1.07
	(1.09)	(1.41)	(2.45)	(6.56)	(2.27)
Percent Cardiologist	0.11	0.16	0.30	0.76	0.29
	(0.32)	(0.36)	(0.46)	(0.42)	(0.45)
Number of peer providers	22.52	24.20	34.91	61.83	46.23
	(26.68)	(29.86)	(36.23)	(43.16)	(39.99)
Total own payment, $	0.00	28.37	186.96	20,344.53	287.17
	(0.00)	(25.42)	(157.90)	(33,579.86)	(4,026.77)
Number of quarters:					
with own pay (out of 10)	0.00	2.33	5.39	7.73	2.02
	(0.00)	(1.67)	(2.87)	(2.63)	(2.98)
with peers paid over $300 (out of 10)	1.01	1.05	1.64	2.66	5.26
	(2.46)	(2.51)	(3.06)	(3.54)	(3.13)
Number of observations (physician x drug x quarter)	1,776,352	563,800	564,024	15,608	647,624

Figure 3: Summary Statistics of Different Types of Pharmaceutical Payment



Notes: The number of payments (count), mean payment in dollars, and total dollar volume of all payments for each of the main types of payments in our sample. Compensation for services include speaking fees. Source: authors' calculations based on all 2014–2015 payments associated with Anticoagulant drugs in Open Payments data.

Figure 4: Average Payments to Physician, by Drug and Medical Specialty



Notes: The average cumulative payments associated with each drug that were made to primary care physicians and cardiac specialists during the study sample period. Source: Authors' calculations based on Open Payments and Physician Compare data.

A Online Appendix

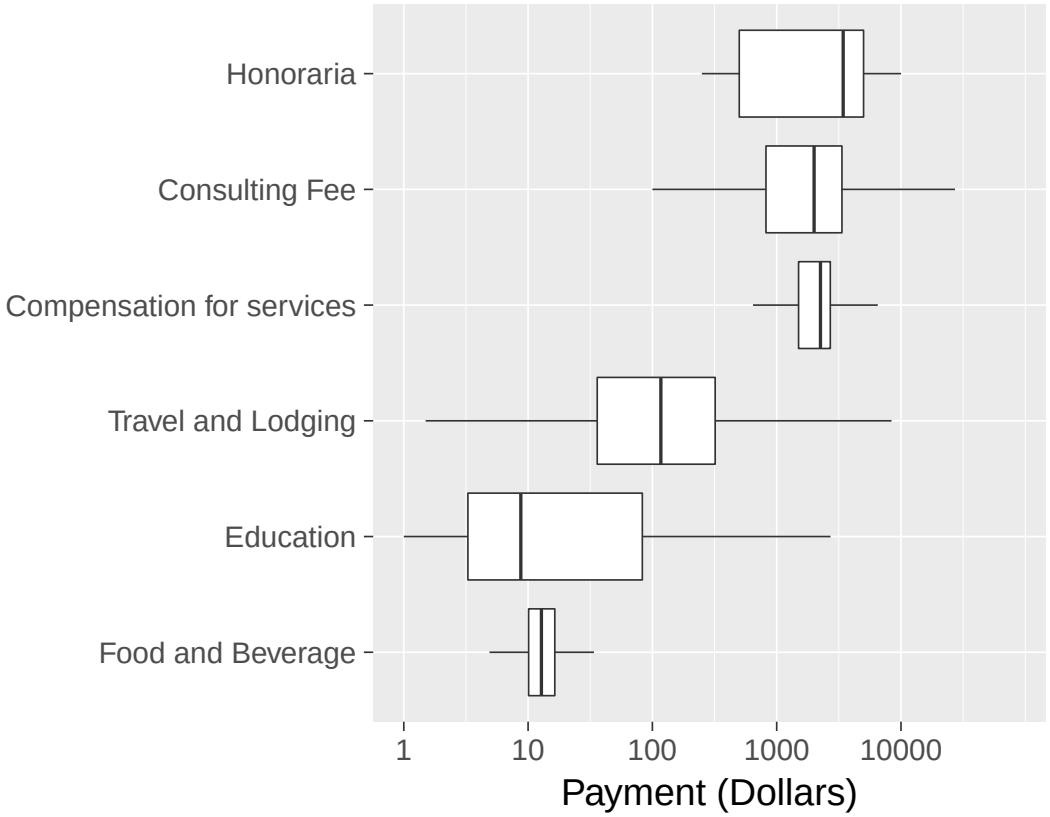
Additional Tables and Figures

Table A1: Descriptive Statistics: Number of Shared-Patient Peers

	Category	Mean	Se	10%	25%	50% (median)	75%	90%
Primary Specialty								
	Primary Care	17.100	0.049	1	4	11	24	42
	Cardiac Specialist	60.200	0.288	12	28	53	84	116
Gender								
	Female	15.700	0.087	1	3	8	21	40
	Male	26.000	0.088	2	6	15	35	64
Graduation Year								
	(1942,1983]	22.800	0.139	2	5	12	28	59
	(1983,1994]	24.000	0.133	2	5	13	31	61
	(1994,2003]	23.800	0.125	2	5	14	34	57
	(2003,2015]	18.800	0.126	1	4	11	28	46
Total		22.800	0.067	2	5	13	31	57

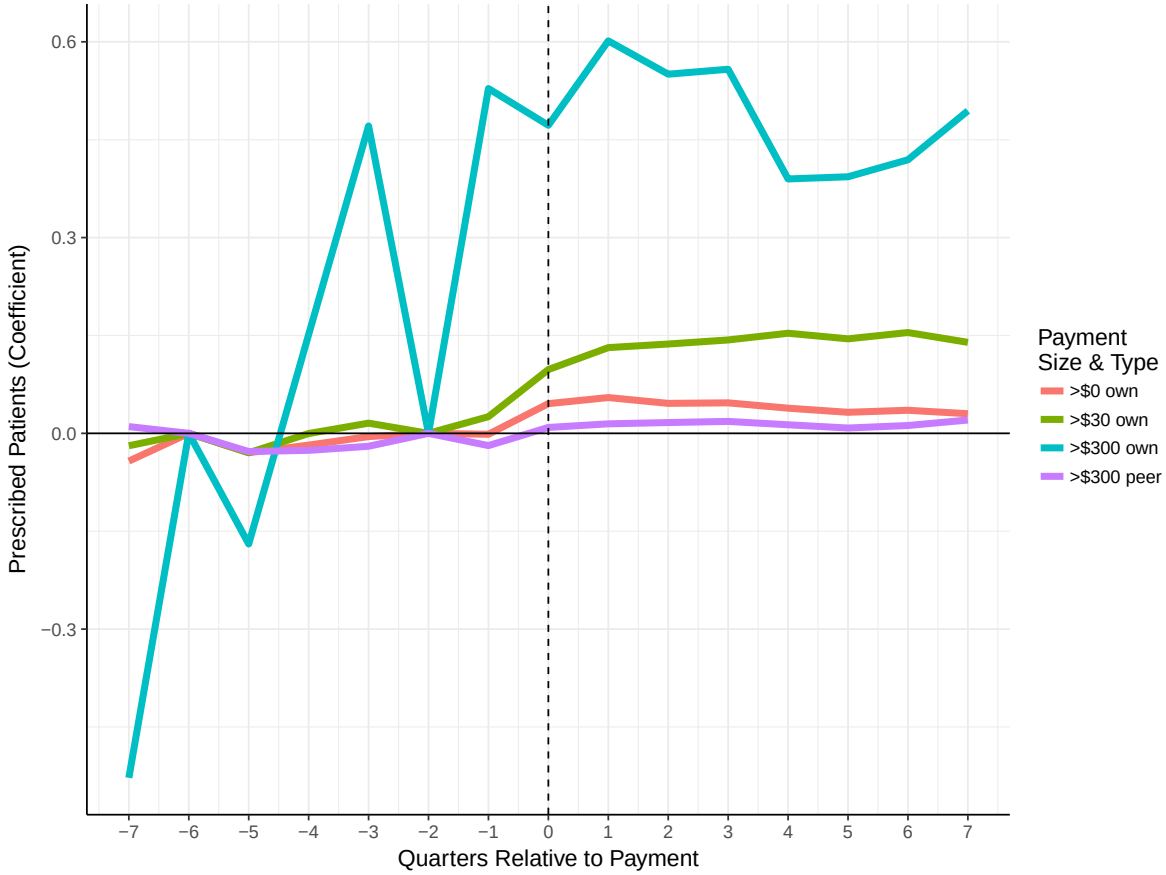
Notes: Number of shared-patient peers in 2013, for all physicians of at least one peer. N=171,000. Source: authors' calculations using CMS data.

Figure A1: The Nature and Size of Payments to Physicians



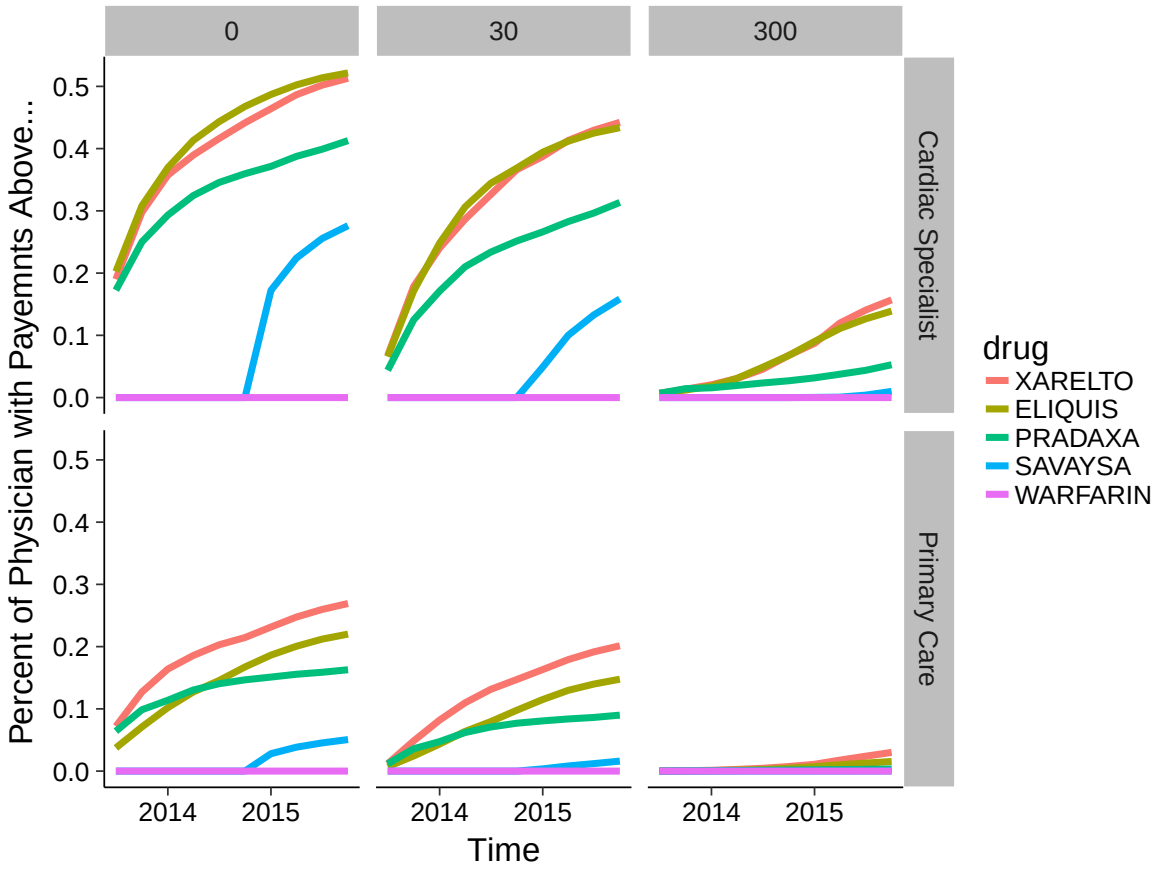
Notes: Boxplot of payment size by payment nature (type), for all payments associated with anticoagulant drug that were made to during the study sample period. Source: Authors' calculations based on Open Payments.

Figure A2: Event Study, Including Large Payments



Notes: Reproduction of Figure 2, with > $300 own payments included.

Figure A3: Fractions of Physicians Paid, by Drug and Medical Specialty



Notes: The cumulative fraction of physicians whose cumulative payments associated with each drug that were made to primary care physicians and cardiac specialists during the study sample period were above different thresholds. Source: Authors' calculations based on Open Payments and Physician Compare data.