The Role of Physician Social Networks in Receipt of Pharmaceutical Industry Payments

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ABSTRACT

Importance: Financial relationships between physicians and the pharmaceutical industry are common, but the factors associated with physicians receiving payments are unknown.

Objective: To evaluate the influence of physicians' shared patient networks and individual characteristics on the receipt of payments among physicians.

Design: Cross-sectional network analysis.

Setting: US physicians for Medicare patients in 2015.

Participants: US physicians who shared Medicare patients with other physicians in 2015.

Exposure: Proportion of a physician's shared patient network that received industry payments and other network characteristics including degree (number of physician connections), centrality (how central the physician is within the network), and transitivity (the density of the referral network in which a physician is located).

Main Outcome Measures: Relative risk of receiving industry payments. We used modified Poisson regression to control for confounding by gender, time since graduation, practice size, and practice setting (teaching hospital vs. not). We included fixed effects for specialty and hospital referral region level.

Results: The proportion of a physician's peers that received payments was strongly associated with receipt of payments by the physician (top vs bottom quartile aRR=1.28, 95%CI=1.24-1.31, p-value<0.01). Physician's number of ties had a small negative effect on receiving payments (top vs bottom quartile aRR=0.98, 95%CI=0.96-1.00, p-value=0.03). Transitivity (i.e., network density) also had a small negative association with receipt of payments (top vs bottom quartile aRR=0.97, 95%CI=0.96-0.98, p-value<0.01). We found many physician characteristics associated with an increased risk of receiving payments including gender (men vs women aRR=1.10, 95%CI=1.09-1.11; p-value<0.01), age (aRR=0.94, 95%CI=0.93-0.95, p-value<0.01 when comparing those graduating before 1985 to those who graduated 2002 and after), and association with a teaching hospital (aRR=1.02, 95%CI=1.01-1.04, p-value<0.01).

Conclusions and Relevance: Network characteristics, particularly the receipt of payments among physicians one shares patients with, influence whether a physician receives payments. This finding has implications for institutional regulation of industry payments to physicians and demonstrates how institutional policy may impact not only the physicians within the institution but also physicians outside of the institution.

INTRODUCTION

Financial relationships between physicians and the pharmaceutical industry have become increasingly commonplace within the United States (US). A 2009 Institute of Medicine report suggested that such relationships represent conflicts of interest that threaten the "quality of patient care, and the public's trust in medicine."[1] Scientific investigation has given increasing credence to such concerns, suggesting that financial relationships with industry influence physician behavior in potentially inappropriate ways. Physicians with industry relationships interpret clinical trial results more favorably[2] and are more likely to recommend specific drugs when writing clinical practice guidelines.[3] Additionally, industry payments may directly influence patient care by increasing physicians' prescription of higher-cost, brand-name, and/or inappropriately-used pharmaceuticals.[4-9] Even small gifts (e.g., $20 meals) have been associated with increased prescribing of a company's drugs.[7]

The Open Payments Provision of the Affordable Care Act (also known as the "Sunshine Act") recently mandated public reporting of all financial payments between the pharmaceutical industry and US physicians and teaching hospitals, facilitating research on the relationship between industry payments and clinical care. Industry payments valued as low as $10 are included in this public record, which is reported annually and made available for free download by the Centers for Medicare and Medicaid Services (CMS).[10]

Prior research has focused on how receiving industry payments impacts physician behavior. However, the literature has largely failed to explore which physicians receive payments. We hypothesize that physicians' social networks may influence physicians receiving industry money. Based on evidence suggesting that physicians who share patients are more likely

to have a recognized professional relationship, we measure physicians' social networks using shared-patient relationships from claims.[11-13]

Physicians' role in networks may influence receipt of industry payment in many ways. First, physicians may be more likely to accept industry money if their peers also accept industry money due to social norms. Alternatively, physicians who accept money from industry may choose to work in practices that encourage receipt of industry funds (i.e., homophily). Second, if physicians are important within a network, then industry may target them since they may be able to influence their colleagues' behavior. Influence can be measured in network analysis as how central an individual is within a network. Additionally, any individual physician may be less likely to be targeted by industry in dense, tightly connected networks because information would already spread quickly in such networks. Despite the importance of the social environment, little to no research has explored the influence of physicians' social network on receiving money from industry. This study uses established methods from the network sciences to examine how network characteristics influence the receipt of payments among physicians.

METHODS

Data Sources

Industry Payments: Open Payments data contains all transfers of financial value greater than $10 from US drug and device manufacturers to physicians and teaching hospitals. Payments are categorized as "general payments" , including gifts, consultancy/speaker fees, meals, and travel; "research payments", including any payments associated with preclinical research, FDA phase I-IV trials, or investigator-initiated studies; and "ownership interests," including stocks, bonds, and partnership. Each financial transaction includes descriptors such as date, type of payment,

industry payer, and recipient physician/hospital.[10] For this study, we examined the association of general payments only and any further reference to industry payments exclusively refers to general payments.

Physician Compare: CMS publicly releases data on physicians' characteristics as part of the Physician Compare initiative.[14] We used this information for physician characteristics including gender, practice size, graduation year, and location. We used the 2017 Physician Compare file as it contains information about physician characteristics recorded in 2015.

Physician Shared Patient Networks: We used CMS Physician Shared Patient Patterns (PSPP) files.[15] These records were created by CMS and were constructed with Medicare claims housed in the CMS Integrated Data Repository to identify physician patient sharing networks. Each physician sharing relationship is recorded within the data by counting the number of shared patients over a 30-day window and the number of unique patients within a 30-day window. These counts are aggregated over the course of the year. CMS includes only physician pairs that shared 11 or more patients over the course of a year.

Linking Between Datasets: We obtained data from all sources for calendar year 2015 and linked across all datasets. First, we linked the Open Payments data to the CMS National Plan and Provider Enumeration System (NPPES), a record of the full universe of providers billing CMS, to identify the quality of the overall linkage. Because there is no common physician identifier between the Open Payments data and all other files, including NPPES, we used the recorded provider name and practice location (state, city and zip code) to link datasets similar to the

methods described by DeJong et al[7]. We then merged this data to the Medicare Physician Compare file and Physician Shared Patient Patterns data using the National Provider Identifier (NPI) (see Appendix Figure A).

Measures

Primary Outcome: The primary outcomes for this study were the receipt of any payments from industry and receipt of payments of $100 or more from industry in 2015.

Identifying Physician Networks: Using the Physician Shared Patient Patterns, we created physician-to-physician networks, which connect each physician to each other through shared patients. When there are any shared patients between two physicians this is referred to as a "tie" between the two physicians. We created geographically-based physician networks within hospital referral regions (HRR).[16,17] We dropped any observations where the ties between physicians spanned two HRRs. This resulted in 309 geographically based physician networks. After networks were created, we dropped physicians that had only one tie with another physician since transitivity (a network metrics that measures density) requires more than one tie for calculation (N=45,938, 11% of physicians).

Network-Based Metrics

Degree: The strength, or value, of the tie can be determined by assessing the number of patients the physicians shared. We assess how connected a physician is by summing the number of ties a physician had, weighted by the value of these ties, to determine the "valued degree" (i.e., if a physician shared 12 patients with each of 4 other physicians, the total degree for that physician would be 48).

Centrality: To quantify a physician's centrality and influence within her network, we calculated the betweenness centrality. Betweenness centrality is measured by counting the number of times a physician is on the shortest path between the other physicians, divided by all the shortest paths between all the physicians within a network. In the social network literature, individuals who are highly central in a network are often considered to be more influential.[18] Therefore, we hypothesize the highly central individuals will be more likely to be targeted by industry due to their influential nature.

Transitivity: Also known as the clustering coefficient, transitivity describes the density or tightness of a network. It is calculated by examining the proportion of a physician's peers that share patients with each other, with larger numbers indicating increased density.[19] Tight networks may allow for faster spread of information, therefore we expect that industry will not have to target as many people within tight networks since the information will spread rapidly by just targeting a few physicians.

Peer Receipt of Payments: For each physician, we measured the commonality of industry payments among his/her peers, calculated as the proportion of physicians to whom the index physician had ties who received any payments or payments greater than or equal to $100 from industry.[20] We hypothesize that peer receipt of payments will influence physicians' acceptance of payments from industry for many reasons. First, physicians may choose to work with other physicians who are similar to themselves (i.e., homophily). Peers accepting or failing to accept industry payments may also result in a social norm that results in a physician being willing to accept or reject an industry payment.

Covariates: We also measured the following covariates: physician gender, physician specialty, time since graduation, and practice setting (teaching hospital vs other setting). We identified

teaching hospitals based on CMS data and matched the list to the Physician Compare-derived hospital and/or institutional association for each physician.[14]

Statistical Analysis

In order to determine the association between a physician's network characteristics and the receipt of industry payments, we first examined the unadjusted relationship between network characteristics and receipt of payments. We defined quartiles within each HRR for all network metrics (degree, centrality, transitivity, and percent of connected physicians receiving payments) and treated the quartiles as categorical variables. We used a modified Poisson model to estimate the adjusted relative risk of receiving industry payments. Additionally, we used predictive marginal standardization to generate the predicted probability of receiving industry payments.[21] We included fixed effects for HRR and physician specialty and adjusted for all previously listed covariates. Additionally, we clustered standard errors at the HRR level.

Sensitivity Analysis

Robustness of Peer Effect: We conducted a sensitivity analyses to test the effect of peer receipt of payments because peers can influence each other within a year, creating an endogeneity problem referred to as the "reflection problem" in network analysis.[22] We conducted two sensitivity analyses to address this potential bias. First, we examined how prior year's peers' receipt of payments impacts a physician in the current year. The prior year's payments should not suffer from reflection in the current year.[23] Second, we examined physicians that have moved in the prior year (determined by a changing billing zip code) to investigate how their peers from the prior year influence payments in this year.[24] This further protected from the reflection problem by ensuring that prior year peers in another area cannot influence the physician in the

current year. We treated peers' prior year payments as an instrumental variable. We implemented the instrumental variable analysis using a two-stage residual inclusion model.[25]

RESULTS

Unadjusted Results: Of the roughly 365 thousand physicians, we found that 62 percent received a payment of any value and 45 percent received total payments of at least $100 from industry (Table 1). We found that physicians receiving payments were more likely to be men (no payment 69% vs payment 79%; p-value<0.01), were from relatively smaller practices (no payment 22% vs payment 29% in a 0-20 group practice size; p-value<0.01), were older (mean graduating year for no payment recipients 1993 vs for no payment recipients 1991; p-value<0.01), and were more likely to practice at a teaching hospital (for no payment recipients 7% vs for payment recipients 8%; p-value<0.01). When looking at network characteristics, we found that those who received payments were more likely to have many ties (for example 30% of the no payment group vs 25% of the payment group were in the bottom quartile of degree; p-value<0.01), more likely to be central in the network (for example 27% of the no payment group vs 24% of the payment group are in the bottom quartile of centrality; p-value<0.01), and less likely to be part of dense network (for example 26% of the no payment group vs 24% of the payment group are in the bottom quartile of transitivity; p-value<0.01), but were much more likely to have peers that received industry payments (for example 31% of the no payment group vs 22% payment group are in the bottom quartile of peers receiving payments; p-value<0.01).

Adjusted Results: The adjusted results show many physician characteristics were associated with payment receipt (Table 2). We found many physician characteristics associated with an increased

risk of receiving payments including gender (men's aRR=1.10, 95%CI=1.09-1.11; p-value<0.01), practices size (aRR=0.87, 95%CI=0.86-0.89, p-value<0.01 when comparing physicians who practice in groups of 0-20 to groups over 440 physicians), age (aRR=0.94, 95%CI=0.93-0.95, p-value<0.01 when comparing those graduating before 1985 to those who graduated 2002 and after), and association with a teaching hospital (aRR=1.02, 95%CI=1.01-1.04, p-value<0.01).

We found that network characteristics were associated with receiving payments. First, we found a large significant positive association between peers receiving payments and receipt of payments for the physician (top quartile aRR=1.28, 95%CI=1.24-1.31, p-value<0.01 with the bottom quartile of proportion of peers receiving payments as the reference). When examining the predicted probabilities of receiving payments, we saw a consistent dose-response relationship between the proportion of peers that receive payments and the physician herself receiving payments (Figure 1): from 54% in the bottom quartile to 68% in the top quartile. We found a significant small, negative association between the number of ties a physician had and receiving payments when comparing the top to the bottom quartiles (top quartile aRR=0.98, 95%CI=0.96-1.00, p-value=0.03). When examining transitivity (i.e., network density), we observed a consistent negative association; however, moving from the top to bottom quartile only changed the predicted probability of receiving a payment by 1.8% (top quartile aRR=0.97, 95%CI=0.96-0.98, p-value<0.01). We found that centrality was associated with a slight increase in the probability of receiving payments, when comparing the bottom quartile to the top two quartiles (top quartile aRR=1.02, 95%CI=1.02-1.04, p-value<0.01). Again, the predicted probability when moving from the top to bottom quartile only increased the predicted probability of receiving a

payment by 1.8%. All of these results were consistent when we treated receipt of payments over $100 as the outcome.

Sensitivity Analysis: In additional analyses that examined the influence of only ties from the prior year, or of only ties from the prior year among physicians that moved, the association between physicians' peers' receipt of payment and a physician's own receipt of payment were still large and significant. The relative risks for the proportion of over half of peers receiving payments was 1.22 (95%CI=1.20-1.24, p-value<0.01) and 1.21 (95%CI=1.16-1.26, p-value<0.01), respectively.

DISCUSSION

Our results suggest that physicians' network characteristics may be an important determinant of whether physicians receive industry payments. As one may expect, physicians' direct (first-order) ties had the largest influence on receipt of payments. We tested this relationship to try to overcome reflection bias and found similar results. We found that other network characteristics also influenced receiving payments. First, as physicians became more central they were more likely to receive payments, and as network density increased physicians were less likely to receive payments. However, these relationships were relatively small in magnitude. Counter to our hypothesis, we did not find a consistent association with the number of physician ties, as measured by degree, and receipt of payments. In addition to network characteristics, consistent with prior work, we found that men, those in small practices, older physicians, and those in teaching hospitals were more likely to receive payments.[26]

Prior work has consistently documented that receiving payments influences prescribing;[1] however, there is little work that has documented what influences whether a physician will receive payments. Prior work has examined some factors, such as the strength of a hospital's

conflict of interest policy, and has found that conflict of interest policy is not associated with receiving payments.[26] This study just begins to document factors that are associated with payment receipt.

This study has several limitations. First, our study relied on Open Payments data for identification of receipt of payments. Recent research has highlighted that this source may underreport physicians' receipt of payments.[27] Second, we constructed our physician networks based on Medicare data; therefore, the networks of physicians may vary when including non-Medicare patients. However, this data in unique in its completeness of capturing all Medicare interactions, whereas prior work has had to construct networks based on much smaller geographic samples.[11-13] Third, we created networks based on physician sharing a patient within a 30 day timeframe. Recent work has tested if networks should be constructed from all mutual patients between physicians, or from the subset of mutual patients treated by both physicians for related health conditions; both approaches were found to be reasonable and can be used for network analysis.[28] Fourth, we do not capture many physician characteristics that may be relevant such as a physician's reputation, physical proximity between physicians, and friendships between physicians.

Our study illustrates the complexity of the relationship between network characteristics and industry payments. This study is not able to identify the causal mechanism underlying this association; it is not clear whether industry preferentially targets opinion leaders or well-connected physicians, or if more important and well-connected physicians more actively seek out and secure payments. However, our results suggest that network characteristics, particularly the receipt of payments among physicians one shares patients with, influence whether a physician chooses to receive payments. This finding has implications for institutional regulation of industry

payments to physicians. Specifically, if an institution changes the rules around whether physicians can receive industry payments, this may impact not only the physicians within the institution but also physicians outside of the institution that are professionally connected to physicians within the organization.

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Table 1. Descriptive Characteristics Overall and by Receipt of Payments

	Overall	No Payment	Payment	P-Value
N	365,097	139,718	225,379	
Male	75.03%	69.15%	78.67%	<0.01
Total Payments	2781 (33,800)	0	4504 (42,929)	<0.01
Received Over $100 in Payments	45.17%	0	73.17%	<0.01
Practice Size, Mean (Std Dev)	378 (681)	498 (804)	305 (575)	<0.01
0-20	26.03	21.50	28.84	<0.01
21-119	22.61	22.15	22.90	
120-439	17.05	17.08	17.03	
440+	34.31	39.27	31.23	
Graduation Year	1991.8 (11.2)	1993.1 (11.4)	1990.9 (11.0)	<0.01
<1985	27.71	24.76	29.55	<0.01
1986-1994	28.01	26.02	29.25	
1995-2001	20.59	20.54	20.62	
2002+	23.68	28.67	20.58	
Teaching Hospital, %	7.34	6.57	7.82	<0.01
Network Characteristics				
Degree	38.46 (55.28)	38.60 (61.65)	38.38 (50.93)	0.23
Quartile 1	26.51	29.50	24.66	<0.01
Quartile 2	24.17	23.35	24.67	
Quartile 3	25.59	22.84	25.67	
Quartile 4	24.73	24.31	24.99	
Centrality	4830.53 (35863.67)	5873.04 (43003.87)	4184.25 (30594.45)	<0.01
Quartile 1	24.99	27.35	23.53	<0.01
Quartile 2	24.95	25.09	24.86	
Quartile 3	25.07	23.30	26.17	
Quartile 4	24.99	24.26	25.44	
Transitivity (Clustering Coef)	0.69 (0.27)	0.69 (0.28)	0.69 (0.29)	0.50
Quartile 1	25.02	26.21	24.27	<0.01
Quartile 2	24.98	22.53	26.50	
Quartile 3	26.15	25.77	26.39	
Quartile 4	23.85	25.48	22.83	

% 1st Degree Ties with Payments	56.67%	51.22%	60.04%	<0.01
Quartile 1	25.92%	31.52%	22.44%	<0.01
Quartile 2	24.81%	25.30%	24.50%	
Quartile 3	24.84%	21.84%	26.70%	
Quartile 4	24.44%	21.34%	26.36%	
% 1st Degree Ties with Payments >100	39.21%	34.01%	42.43%	<0.01
Quartile 1	25.84%	31.36%	22.41%	<0.01
Quartile 2	25.12%	25.60%	24.82%	
Quartile 3	24.76%	2235%	26.26%	
Quartile 4	24.28%	20.70%	26.50%	

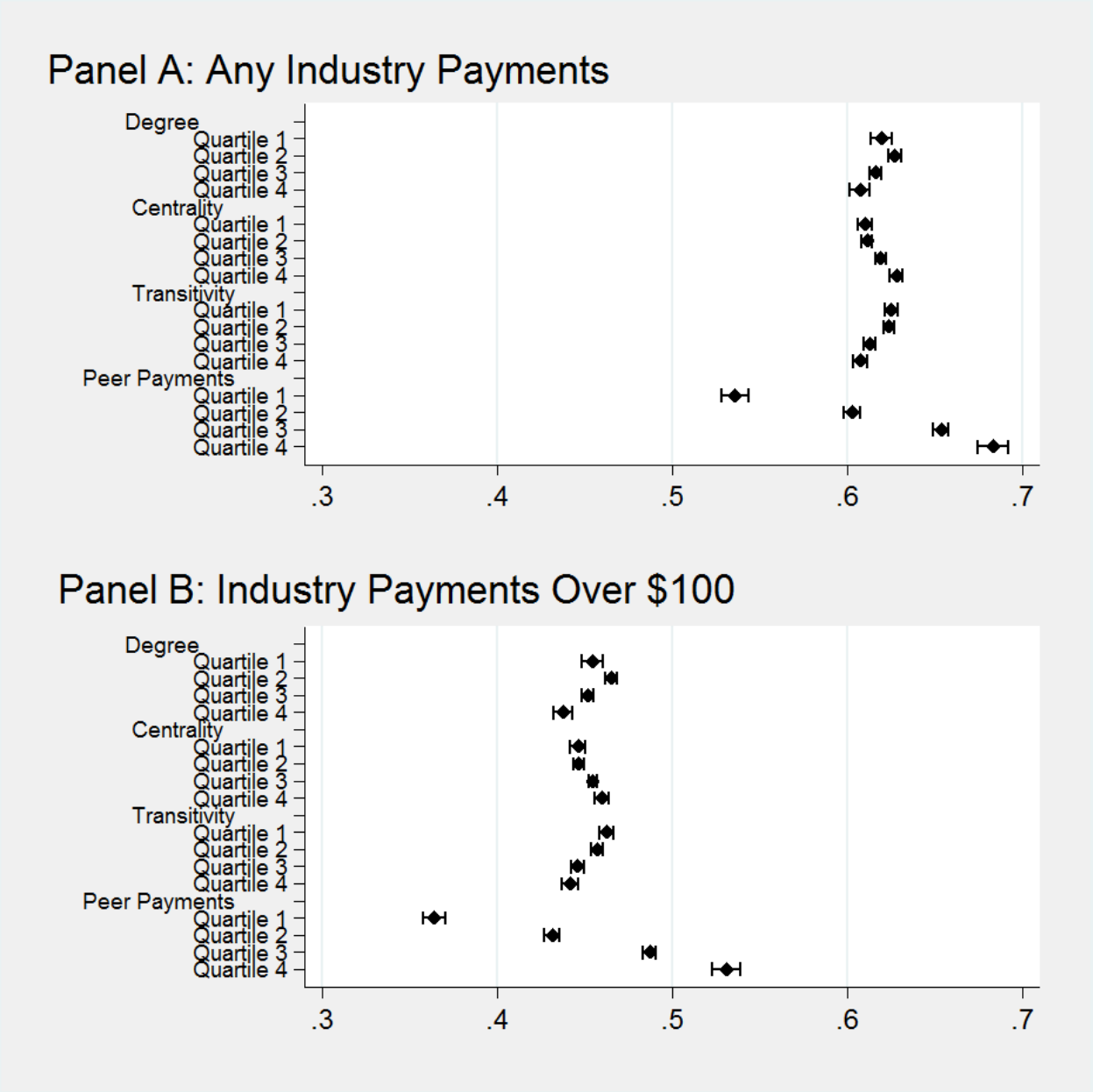
Table 2. Adjusted Associations Between Physician and Network Characteristics and Receipt of Payments

	Any Payment	P-Value	Payment Over 100	P-Value
Male	1.10 (1.09, 1.11)	<0.001	1.16 (1.14, 1.18)	<0.001
Practice Size				
0-20	Reference		Reference	
21-119	0.95 (0.93, 0.96)	<0.001	0.90 (0.89, 0.92)	<0.001
120-439	0.91 (0.89, 0.93)	<0.001	0.86 (0.84, 0.88)	<0.001
440+	0.87 (0.86, 0.89)	<0.001	0.84 (0.82, 0.86)	<0.001
Graduation Year				
<1985	Reference		Reference	
1986-1994	1.03 (1.02, 1.03)	<0.001	1.06 (1.05, 1.07)	<0.001
1995-2001	1.01 (1.00, 1.01)	0.160	1.03 (1.02, 1.04)	<0.001
2002+	0.94 (0.93, 0.95)	<0.001	0.96 (0.94, 0.97)	<0.001
Teaching Hospital, %	1.02 (1.01, 1.04)	0.013	1.03 (1.00, 1.05)	0.033
Network Characteristics				
Degree				
Quartile 1	Reference		Reference	
Quartile 2	1.01 (1.00, 1.02)	0.011	1.02 (1.00, 1.03)	0.016
Quartile 3	0.99 (0.97, 1.00)	0.489	0.98 (0.96, 1.00)	0.062
Quartile 4	0.98 (0.96, 1.00)	0.033	0.95 (0.92, 0.97)	<0.001
Centrality				
Quartile 1	Reference		Reference	
Quartile 2	1.00 (0.99, 1.01)	0.661	1.00 (0.99, 1.01)	0.864
Quartile 3	1.01 (1.01, 1.02)	0.003	1.02 (1.01, 1.03)	0.004
Quartile 4	1.02 (1.02, 1.04)	<0.001	1.03 (1.01, 1.05)	<0.001
Transitivity				
Quartile 1	Reference		Reference	
Quartile 2	0.99 (0.99, 1.01)	0.563	0.99 (0.98, 1.00)	0.064
Quartile 3	0.98 (0.97, 0.99)	<0.001	0.97 (0.95, 0.98)	<0.001
Quartile 4	0.97 (0.96, 0.98)	<0.001	0.96 (0.94, 0.97)	<0.001
% 1st Degree Ties with Payments				
Quartile 1	Reference			
Quartile 2	1.12 (1.11, 1.14)	<0.001		
Quartile 3	1.23 (1.20, 1.24)	<0.001		

Quartile 4	1.28 (1.24, 1.31)	<0.001		
% 1st Degree Ties with Payments >100				
Quartile 1			Reference	
Quartile 2			1.19 (1.17, 1.20)	<0.001
Quartile 3			1.34 (1.31, 1.37)	<0.001
Quartile 4			1.46 (1.42, 1.50)	<0.001

Note: Models also included fixed effects based on the hospital referral region and specialty of the provider. Standard errors clustered at the hospital referral region.

Figure 1: Predicted Probability of Receiving Payments



Appendix Figure A: Analytic Dataset Creation