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Identifying physician peer-to-peer effects using patient movement data

Tulikaa Bhatia [a,*], Lei Wang [b,1]

[a] Rutgers Business School, Department of SCMMS, 94 Rockafeller Road, Piscataway, NJ 08854, United States
[b] Rutgers Business School, Department of SCMMS, 1 Washington Park, Newark, NJ 07102, United States

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ABSTRACT

In this paper, we identify and quantify peer-to-peer effects using physician prescription data and patient movement data between physicians. We categorize the movements into three types: 1) primary care physician (PCP) to specialist and back, 2) specialist to specialist, and 3) PCP to PCP. In-depth physician interviews and surveys reveal different reasons for these movements: PCP to PCP is purely patient-generated; PCP to specialist is mostly physician-generated; and specialist to specialist is a mix of patient- and physician-generated movements. We estimate a simultaneous equations model on these three types of movements and find that in the purely patient-generated movement sample (PCP to PCP), the physicians have a significantly negative effect on each other's prescription behavior due to *observational learning* and *congestion* effects. In contrast, in the PCP to specialist sample and the specialist to PCP sample, we find that the specialist has a significantly positive effect on the PCP but not *vice versa*. This result suggests an *opinion leader* effect. Specialist to specialist movement is a mixed case, and the effect is insignificant in most cases. Based on model estimates, we calculate the social multiplier to quantify the effect of opinion leaders on other physicians in the sample. We find focal specialists who are high prescribers are more likely to be opinion leaders.

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1. Introduction

Interest in tapping customer networks to increase revenues in mature markets has been growing exponentially. Marketers have tried to exploit the potential of online peer-to-peer networks using viral marketing campaigns (De Bruyn & Lilien, 2008). Firms track how consumers interact in online social networks to target these consumers better (Steel, 2010). There has also been an increase in loyalty programs and 'referral' marketing, which involves a deliberate, structured program of soliciting and rewarding referrals from current customers. The key to better utilizing consumers' social networks is to understand their structure and how their members influence each other.

In this research, we try to quantify peer-to-peer effects using observable transaction data. We use the context of the pharmaceutical industry for this research. The identification of opinion leaders in physician networks is a substantial opportunity for pharmaceutical firms that, faced with declining returns, are making several changes to the traditional sales channels. First, pharmaceutical firms have streamlined the traditional 'one-size fits all' model. The overall size of the industry's U.S. sales force declined 10% to about 92,000 in 2008 from a peak of about 102,000 in 2005. All major US pharmaceutical firms have made significant reductions in sales force headcount since 2006, with potentially more reductions to come (Pettypiece & Alesci, 2009). In addition, firms are pulling back on Direct to Consumer spending. For example, GSK plans to cut back advertising on TV in 2009 (Whalen, 2009). Second, pharmaceutical firms are making refinements to how the sales model works at the regional level by giving greater autonomy to regional sales forces. 'Local peer-to-peer networks' offer a significant opportunity for pharmaceutical firms to improve the effectiveness of marketing to physicians.

While the national key opinion leaders are well respected as academicians/thought leaders who publish in leading journals, physicians have a stronger referral relationship with local opinion leaders. In addition, physicians' interactions with national key opinion leaders are not sustained in nature because these leaders are not local. Identifying peer-to-peer networks at the local territory/district level is a key hurdle limiting impact and adoption of a localized sales model. Information typically resides in the field and is not compiled for usage because there is limited bandwidth and there are no consistent sets of criteria applied by sales representatives. Additionally, there is no one-stop information source to provide detailed network information at the local territory/district level. To complicate matters further, these networks of influence differ by therapeutic area. The focus of this paper is on identifying the '*market leaders*' who are closely connected to the local physician population and not the '*clinical leaders*' who are identifiable at the national level (Stremersch & Van Dyke, 2009).

Key opinion leader selection in the life sciences has been identified as a critical decision area by Stremersch and Van Dyke (2009) because

* Corresponding author. Tel.: +1 732 445 5274; fax: +1 732 445 5946.
E-mail addresses: tulikaa@rci.rutgers.edu (T. Bhatia), Lei-wang@business.rutgers.edu (L. Wang).
[1] Tel.: +1 973 353 1605; fax: +1 732 445 5946.

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it is of importance to both business performance as well as patient welfare. There has been related research recently in asymmetric peer effects (Iyengar et al., 2010; Nair, Manchanda, & Bhatia, 2010) showing the existence of opinion leaders in the pharmaceutical industry. Both of these papers use self-reported surveys to identify opinion leaders, which leaves some gaps as to the identification of 'market leaders' at the regional level because the national opinion leaders or 'clinical leaders' tend to be cited by most physicians. Additionally, using survey data has several disadvantages, such as self-reported bias of the physicians, an incomplete list of opinion leaders because only a few physicians fill out the survey, and possibly non-response bias because the physicians filling out the survey may have more time or may be more responsive to detailing (the providing of drug information by pharmaceutical sales representatives).

To identify regional physician peer-to-peer effects, we assemble a unique dataset combining physician prescription data and patient movement data. We do not observe actual interactions between physicians; rather, we observe patient movement between physicians. We try to find links between members (physicians) in a patient movement database using physician surveys to guide us. The patient movements between physicians can be physician-generated or patient-generated. Based on physician in-depth interviews and a physician survey whose results are summarized in Appendix A, we categorize the movements between primary care physicians (PCPs) as being patient-generated. Disgruntled patients move to new physicians if they are not happy with the treatment they are receiving from their current physician. However, the patient movements between primary care physicians (PCPs) and specialists (and *vice versa*) are most likely physician referrals, which reflect the physician network. Because medicine has to be individualized for each patient depending on that particular patient's medical history, age, gender, race, and other concurrent diseases, primary care physicians may often need help from a specialist in deciding the best course of treatment for some patients. There may also be a need for these referrals in certain advanced cases of disease or in cases of medical complications. However, we cannot exclude the possibility that such movement is not due to a referral but due to a patient decision because we do not have such additional information as patient insurance. Our empirical strategy to identify the opinion leader effect is to show that the peer-to-peer effect from patient-generated movement is different in direction and sign from the effect identified from the mostly physician-generated movement data. The specialist to specialist movements are a mixed case of patient-generated and physician-generated movements. Some patients may be disgruntled with their specialists and may move to other specialists, while some may be referred to other specialists.

To identify the causal peer-to-peer effect, we need to control for other potential hypotheses. Similar behavior among group members could be due to endogenous interactions, contextual interactions, or correlated effects (Hartmann et al., 2008; Manski, 2000). We model simultaneity in prescriptions, controlling for physician and time period fixed effects and other observed and unobserved factors in the environment that may lead to contextual interactions or correlated effects.

Our paper makes a unique contribution in several ways. First, we offer an innovative way to assemble and structure data to estimate physician peer effects when the social interactions are not directly observed. We divide the patient movements into patient-generated and mostly physician-generated movements based on a physician survey. This categorization helps us to measure different peer-to-peer effects that depend on the nature of the patient movement. Second, we offer a practical methodology for pharmaceutical firms to identify 'market leaders' (Stremersch & Van Dyke, 2009) by using the now-available anonymous patient level data (APLD) from vendors. This methodology is faster, less expensive, and provides wider coverage than asking physicians to nominate opinion leaders. It has direct applicability for pharmaceutical firms whose sales forces can make more effective judgments armed with this physician network information. Third, our paper provides evidence for improving allocation of marketing resources. Current practice in the industry is based on targeting heavy prescribers. However, we find that the opinion leaders in the category examined are specialists who are low prescribers compared to PCPs. Pharmaceutical firms can increase sales by allocating more resources to these specialists with higher social multipliers.

The rest of the paper is organized as follows: Section 2 discusses the relevant literature, followed by the description of the data and the model in Sections 3 and 4, respectively. We discuss the results from estimating the model in Section 5, the managerial implications in Section 6, and the conclusions in Section 7.

2. Existing literature

There is a substantial amount of literature in sociology, marketing, and economics on social networks. Most of the literature in marketing is focused on the diffusion of innovations and word-of-mouth based on the Bass model (1969) and its multiple extensions. This stream of research focuses on aggregate-level diffusion, and our research focuses on identifying the peer effects at an individual level. Our work is related to the literature on social networks, such as Coleman, Katz, and Menzel (1966), Burt (1987), Van den Bulte and Lilien (2001), and Manchanda, Xie, and Youn (2008). The Medical Innovation Study (Coleman et al., 1966) in sociology was among the first to focus on whether there are opinion leaders. The study was followed by Burt (1987) who used more accurate identification, and Van den Bulte and Lilien (2001), who added marketing variables to the model, while employing the data from the Medical Innovation Study to better identify the social effects.

There has been research in marketing that models social interactions using other categories; examples include a piano tuning service (Reingen & Kernan, 1986), student grade point average (Sacerdote, 2001), automobile purchases (Yang & Allenby, 2003), an internet grocer (Bell & Song, 2007), and a video-on-demand service (Nam et al., 2010). The economics literature models crime rates in neighborhoods (Glaeser, Sacerdote, & Scheinkman, 1996) and desertions in the army (De Paula, 2009), but using aggregate data. Blume (2003) and Brock and Durlauf (2001, 2002) apply mean field theory to check expectations formed by agents about group behavior, and the expectations are consistent with outcomes. There have been economic models of the process of group formation (Bala & Goyal, 2000; Conley & Udry, 2010). The network effects can work in either direction. Most papers show positive effects, but some, such as the one authored by Frank (1985), show negative social effects due to status-seeking. Goldenberg, Libai, and Muller (2010) show how network externalities can actually slow diffusion of innovation. Stremersch, Lehmann, and Dekimpe (2010) suggest that more work is needed on the separation of social contagion and network effects.

A key issue in identifying peer effects is that of defining peers. Manchanda et al. (2008) use physical distance between physicians to identify physician networks. Trusov, Bodapati, and Bucklin (2010) use observed 'friends' lists on online social networking websites to define the network and the activity (log-on data) to estimate the peer effect. Other research uses surveys and/or experiments to identify the effect of opinion leaders; examples include Valente, Hoffman, Ritt-Olson, Lichtman, and Johnson (2003), Lomas et al. (1991), Celentano et al. (2000), Dufflo and Saez (2003), and Bramoulle et al. (2009). Wuyts, Dekimpe, Gijsbrechts, and Pieters (2010) provide a summary of the data used in the literature to study customer network. We do not observe the network, but we use external patient movement data combined with a physician survey to structure the different peer effects.

Hartmann et al. (2008) provide a recent and broad summary of the various models of social interactions. They focus on the identification problem in all non-experimental analyses of social interactions and point out three specific issues: endogenous group formation, correlated observables, and simultaneity. We discuss how we account for each of these in the context of our research in the model formulation section.

Our research is most closely related to the recent research in marketing on identifying opinion leaders and estimating the social multiplier. Nair et al. (2010) and Iyengar et al. (2010) identified the asymmetric peer effects using a self-reported survey of physicians. We use patient movement data guided by a physician survey to identify physician peer effects. This approach allows us to better understand physician peer effects at the regional level (Stremersch and Van Dyke, 2009) and to estimate the social multipliers for these opinion leaders, which can be used in making more efficient allocations of the detailing and sampling resources of the pharmaceutical firms. We compare selected empirical papers that use individual physician level data to identify peer effects in Table 1.

3. Data

This research uses patient movement data from an anonymous patient level data (APLD) vendor for a period of two years from 2001 to 2003 for around 120 drugs from a large therapeutic category. This therapeutic category treats a disease affecting approximately one in four Americans. The patient movement data are recorded at drug stores when a patient fills his/her prescriptions and his/her previous prescription and the current prescription are from two different physicians. The drug under consideration is a combination drug that has been on the market since 1996. The data include patient ID, physician ID, the date when the transactions took place, and the drug class that was prescribed in each case. However, we do not have patient insurance data that might influence patient movement and reflect the physician network. In addition to patient movement data, we also have information on each physician (such as specialty and prescription decile), their monthly prescriptions of the focal drug in this category from 2001 to 2003, and monthly marketing activities targeting these physicians by the pharmaceutical firm (such as detailing and sampling) from 2001 to 2003.

We first estimated our model using all of the patient movements in the state of Michigan. We chose Michigan because it is relatively isolated physically from other states so that there would not be spillovers to physicians in other states. We verified our results by estimating the model in two other states, Texas and Georgia. Again, we were looking for states that are physically separated from others, and this time in the south. We did not choose California or the Northeast because the area is too large and the metropolitan statistical areas will have spillovers, making it difficult to isolate the effects.

The descriptive statistics for Michigan, Georgia, Texas, and the national level are tabulated in Table 2. We grouped the physicians into *starting physicians* (the physician the patient/s move from) and *ending physicians* (the physician the patient/s move to). We further grouped them into PCPs and specialists. The descriptives look very similar for the *starting physicians* and the *ending physicians*, but there is a large difference in the number of prescriptions and the prescription deciles of the specialists and the PCPs. In the Michigan sample, the PCPs prescribe much more than the specialists ($p<0.001$ for both starting and ending physicians) and hence have higher prescription deciles than the specialists ($p<0.001$ for both starting and ending physicians) because the PCPs are the primary contact for the patients and treat most patients with the disease in question. Consequently, the PCPs are detailed and sampled much more ($p<0.001$ for both starting and ending physicians) than the specialists by the pharmaceutical firms. The specialists also have a larger number of *starting* and *ending physicians* than the PCPs ($p<0.001$ for both starting and ending physicians). This result suggests that specialists are better connected than PCPs. We also find similar patterns in Texas, Georgia, and at the national level.

The pooled sample contains all physician movements that could be patient-generated or physician-generated, but only the physician-generated movements represent the physician network (Datamonitor, 2008). To better understand the nature of the patient movements, we conducted 12 in-depth interviews and a survey of 18 primary care physicians and 20 specialists (see Appendix A) and found that no PCPs would refer their patients to another PCP, which means that the patient movements between PCPs are patient-generated. Here we would expect that the *ending* PCP would try to avoid doing what the *starting* PCP had done because the patient is most probably unhappy with the treatment provided by the *starting* PCP. Hence we would expect a negative effect of *starting* PCP prescriptions on the *ending* PCP. Because the *starting* PCP loses his/her patient to the *ending* PCP, his/her prescriptions go down due to competition leading to a negative congestion effect.

All PCPs in the survey routinely refer patients to specialists. The specialists then send oral, written, or electronic feedback to the referring PCP—typically within two weeks—conveying to them information including their diagnosis, the drug/s prescribed, and whether they would be seeing the patient again. This is a feedback mechanism through which the PCP can 'learn' from the specialist about treating patients. If the movement is mostly due to physician referrals, we expect to find an asymmetric peer effect between PCPs

Table 1
Literature review of empirical papers investigating peer effects using individual behavioral data.

Paper	Product category	Data/Network	Endogenous group formation	Simultaneity	Targeted marketing variable (Detailing)	Correlated unobservables
This paper (2010)	Pharmaceuticals	Behavioral	Yes	Yes	Yes	Yes
Nair et al. (2010)	Pharmaceuticals	Self-reported + Behavioral	Yes	Yes	Yes	Yes
Iyengar et al. (in press)	Pharmaceuticals	Self-reported + Behavioral	Yes	Yes	Yes	Yes
Trusov et al. (2010)	Online social networks	Self-reported + Behavioral	Yes	Yes	No	Yes
Manchanda et al. (2008)	Pharmaceuticals	Behavioral	Yes	No	Yes	Yes
Van den Bulte and Lilien (2001)	Pharmaceuticals	Self-reported + behavioral	No	No	No	No
Strang and Tuma (1993)	Pharmaceuticals	Self-reported + behavioral	No	No	No	No
Burt (1987)	Pharmaceuticals	Self-reported + behavioral	No	No	No	No
Coleman et al. (1966)	Pharmaceuticals	Self-reported + behavioral	No	No	No	No
Conley and Udry (2010)	Agriculture	Self-reported + behavioral	Yes	No	No	Yes
Sorensen (2006)	Health Plan Choice	Behavioral	No	Yes (by focusing only on new hires)	No	Yes
Sacerdote (2001)	Student Grade Point Average	Location (Dorms)	Yes	No	No	No
Bertrand, Luttmer, and Mullainathan (2000)	Welfare Plan Participation	Cultural distance	Yes	Yes	No	Yes
Reingen and Kernan (1986)	Piano Tuning Service	Self-reported	No	No	No	No

Table 2
Descriptive statistics.

Variable	National		Michigan		Georgia		Texas	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Starting physicians[a] *PCPs*								
Detailing (# of salesperson visits/month)	0.2890	0.5312	0.3331	0.5728	0.3699	0.5934	0.3657	0.5517
# Samples/month	11.57	121.84	8.21	29.87	14.20	29.02	16.03	28.31
# Prescriptions/month	0.1342	0.5145	0.0954	0.3816	0.2204	0.6501	0.2814	0.7440
Category prescription decile[c]	3.70	2.78	3.65	2.68	3.86	3.11	3.76	2.81
# Starting physicians[d]	2.77	2.79	2.01	1.99	3.91	3.81	3.02	2.93
# Ending physicians[e]	3.23	2.57	2.46	1.78	4.16	3.35	3.50	2.75
Number of physicians	74,153		2294		2701		5032	
Starting physicians[a] *Specialists*								
Detailing (in # of salesperson visits/month)	0.1088	0.3135	0.1265	0.3501	0.0776	0.2702	0.1278	0.3367
# Samples/month	3.69	15.07	3.18	11.46	3.20	17.75	4.69	18.38
# Prescriptions/month	0.0462	0.2978	0.0409	0.2643	0.0618	0.4408	0.0853	0.3865
Category prescription decile	2.28	2.27	2.39	2.37	1.95	2.23	2.36	2.36
# Starting physicians	3.40	4.66	2.82	3.61	3.46	5.79	3.69	4.96
# Ending physicians	3.61	3.90	3.13	3.17	3.74	4.66	3.84	4.05
Number of physicians	40,670		1150		2025		2782	
Ending physicians[b] *PCP*								
Detailing (in # of salesperson visits/month)	0.2926	0.5327	0.3338	0.5648	0.3923	0.6039	0.3736	0.5578
# Samples/month	11.65	122.86	7.94	28.55	14.95	29.22	16.18	28.71
# Prescriptions/month	0.1348	0.5093	0.0957	0.3823	0.2321	0.6596	0.2833	0.7455
Category prescription decile	3.71	2.79	3.70	2.68	4.01	3.12	3.75	2.82
# Starting physicians	3.16	2.57	2.43	1.76	4.36	3.63	3.40	2.72
# Ending physicians	2.91	2.82	2.06	2.02	4.10	3.56	3.21	2.99
Number of physicians	72,845		2271		2541		4933	
Ending physicians[b] *Specialists*								
Detailing (in # of salesperson visits/month)	0.1110	0.3161	0.1238	0.3478	0.0882	0.2858	0.1284	0.3365
# Samples/month	3.74	15.15	3.12	10.86	3.56	18.19	4.76	18.48
# Prescriptions/month	0.0473	0.3010	0.0407	0.2644	0.0656	0.4448	0.0872	0.3897
Category prescription decile	2.28	2.28	2.39	2.39	2.07	2.33	2.36	2.38
# Starting physicians	3.89	4.40	3.26	3.35	4.35	5.80	4.17	4.70
# Ending physicians	3.15	4.19	2.67	3.44	3.63	5.12	3.40	4.34
Number of physicians	40,424		1147		1777		2765	
Number of starting and ending physician pairs	389,070		9250		18,804		28,280	

[a] *Starting physician* is the physician the patient/s move from.
[b] *Ending physician* is the physician the patient/s move to.
[c] Physicians are grouped into prescription deciles (0–10) based on the volume they prescribe, e.g., the top decile 10 consists of the top 10% of physicians in terms of the number of prescriptions.
[d] Number of physicians that the patient/s move from.
[e] Number of physicians that the patient/s move to.

and specialists where PCPs are influenced by the specialists they refer patients to but not *vice versa*. We would expect to see patient movements from PCP to the specialist and then back to the PCP for a referral, but in our data, we observe few complete movements. We believe the movements from specialists to PCPs to be the back leg of physician referrals from PCPs to specialists. Thus, here we still expect an opinion leader effect of specialist on the PCP.

Patient movements between specialists are a mixed case, as suggested in the interview and survey. Specialists usually work together with specialists in different fields to provide treatment for the patient. For example, a cardiologist will work closely with a nephrologist to make sure the patient's kidneys are fine and perhaps with an endocrinologist because there is a high chance that the patient has diabetes if he has a heart problem. Therefore, the specialists will refer patients to specialists in fields other than their own but will usually not refer patients to specialists in their own field. There are exceptions to this rule where specialists will seek second opinions from other specialists in the same field for complex cases or refer the patient to a specialist with a different sub-specialty. Twenty-six percent of our survey specialists would refer patients to specialists in their own field, but this is done more rarely than referrals to specialists in other fields. Additionally, the patients may get referrals for the other specialist from their PCP, and there may be no relationship between the two specialists. Because this is a mixed case with some patient-generated and some physician-generated movements, the result will depend on the relative magnitude of these different effects.

4. Model

In our data, we observe patient movement from a *starting physician* to an *ending physician*. Given the patient flow, we model the peer effects on prescription behavior between physicians. Suppose there is at least one patient movement from *starting physician i* to *ending physician j* in our data. We then model how physician *i* and *j* influence each other's prescription behavior.

The pair of physicians may behave similarly for several potential reasons. As Manski (2000) points out, similar behavior among group members could be due to endogenous interactions, contextual interactions, or correlated effects. While the first two describe distinct ways in which a person can be influenced by social environments, the last one is not related to the social environment. Endogenous interactions mean that the propensity of a person to behave in some way varies with the behavior of the group. This is the causal peer effect that we try to measure in this paper because it implies a social multiplier, while the contextual interactions and correlated effects do not.

Contextual interactions mean that the propensity of a person to behave in some way varies with exogenous characters of the group. In our context, the group may be exposed to a similar market level time trend, similar marketing activities, or a similar geographic trend. We include time-fixed effects to control for common time trends at the market level. To control for correlations in marketing activities, we include physician-specific detailing and sampling as explanatory variables in the regression. A potential concern with using detailing and sampling variables as controls is that they might be endogenous and correlated with unobserved physician characteristics if physicians are allocated detailing and sampling levels corresponding to their position in deciles. To control for this endogeneity, we include physician fixed effects. The underlying assumption is that after controlling for physician fixed effects, within-physician and across-time detailing and sampling are independent of other physician time-varying factors. This assumption is reasonable because in practice physicians rarely move across deciles over time. To account for the spatial correlation, for each physician in each month, we compute the average number of prescriptions written by all other physicians who are in the same zip code but not in the sample. Essentially, this term proxies for all unobserved time-period and location-specific shocks to prescriptions that are common to all physicians in the same zip code.

The third hypothesis for similar group behavior is the correlated effects: persons in the same group tend to behave similarly because they have similar individual characteristics. In our context, this issue arises if a patient movement is due to a physician referral and the physician chooses to send the patient to another physician with similar prescription tendencies. Then the observed correlation in the behavior of the physician and the referred physician could arise from omitted individual physician characteristics. The included physician-specific fixed effect controls for individual unobserved time-invariant prescription tendency.

To measure the causal peer effect between physicians, we specify a simultaneous equation model, controlling for the context interactions and correlated effects as discussed previously. The simultaneous equation model contains two equations. One equation is for the *starting physician* from whom the patient moves. The other equation is for the ending physician to whom the patient moves. We use detailing and sampling as well as the mean number of prescriptions issued by the other physicians in the same zip code (excluding everyone in the sample) as instruments to address the potential simultaneity concern. The *starting physician*'s detailing and sampling and the mean number of prescriptions issued by the other physicians in the same zip code affect only the prescription of the *starting physician* and can be excluded from the prescription equation for the *ending physician*. Similarly, the *ending physician*'s detailing and sampling and the mean number of prescription issued by the other physicians in the same zip code can be excluded from the prescription equation for the *starting* physician. For each *starting* and *ending physician*, there are inbound and outbound patient flows from or to the other physicians. To control for the influence of the other physicians, we include the mean number of prescriptions issued by the other connected physicians in each equation and use their mean detailing and sampling and the mean number of prescriptions issued by the other physicians in their zip code as instruments.

Based on the previous discussion, we propose the following simultaneous model to estimate the peer effects between pairs of physicians. Suppose there is at least one patient movement from physician *i* to physician *j*. Our specification for physician *i*'s number of prescriptions of the focal drug issued at time *t* is

$$\begin{aligned} y_{it} = {} & \alpha_i + \alpha_1 d_t + \alpha_2 x_{it} + \alpha_3 z^{i}_{-sample,t} + \alpha_4 y_{jt} + \alpha_5 y_{other\_i,t} \\ & + \alpha_6 y_{jt-1} + \alpha_7 y_{it-1} + \varepsilon_{it}. \end{aligned} \tag{1}$$

The corresponding specification for *j*'s number of prescriptions issued is

$$\begin{aligned} y_{jt} = {} & \beta_j + \beta_1 d_t + \beta_2 x_{jt} + \beta_3 z^{j}_{-sample,t} + \beta_4 y_{it} + \beta_5 y_{other\_j,t} \\ & + \beta_6 y_{it-1} + \beta_7 y_{jt-1} + \varepsilon_{jt}, \end{aligned} \tag{2}$$

where

- y_{it} and y_{jt} are the number of prescriptions written by physician *i* and physician *j*, respectively; $y_{other\_i,t}$ is the average number of prescriptions written by the other physicians besides *j* who are linked with physician *i* because of the patient flow; $y_{other\_j,t}$ is the average number of prescriptions written by the other physicians besides *i* who are linked with physician *j* because of the patient flow; and y_{it-1} and y_{jt-1} are the number of prescriptions written by physicians *i* and *j* in the previous time period $t-1$;
- α_i and β_j are the physician fixed effects;
- d_t are the time dummies;
- x_{it} *and* x_{jt} include marketing variables such as cumulative detailing and cumulative sampling of physicians *i* and *j*;
- $z^{i}_{-sample,t}$ and $z^{j}_{-sample,t}$ are the mean number of prescriptions issued by the other physicians in the same zip code as physician *i (and j)* but not in the sample.
- ε_{it} and ε_{jt} are mean zero error terms.

To account for potential correlation between the errors across equations, we use three-stage least square estimation. x_{jt} and $z^{j}_{-sample,t}$ are excluded from the *starting physician* prescription Eq. (1) and serve as instrumental variables for y_{jt}. Similarly, x_{it} and $z^{i}_{-sample,t}$ are excluded from the *ending physician* prescription Eq. (2) and serve as instrumental variables for y_{it}. We also include $x_{other\_i,t}$, $z^{other\_i}_{-sample,t}$, $x_{other\_j,t}$, and $z^{other\_j}_{-sample,t}$ as instrumental variables for $y_{other\_i,t}$ and $y_{other\_j,t}$.

In this specification, α_4 and β_4 are the key parameters that measure the peer effect. The coefficients of the cross-lag variables, α_6 and β_6, measure the delay in the peer effect.

5. Results

We estimate our model on three samples from Michigan, Texas, and Georgia. First, we discuss the estimates from various models for the pooled sample from Michigan, which are given in Table 3 for model comparison. We compare three models: the ordinary least squares (OLS) model with physician fixed effects, the two-stage least squares (2SLS) model using instruments and fixed effects, and our full three-stage least squares (3SLS) model using physician fixed effects and instruments and allowing for correlated errors between the equation for the *starting physician* and the one for the *ending physician*. The physician prescription effect is much stronger in model 3 compared with models 1 and 2 ($\alpha_4 = -0.0437$ in model 3 vs. -0.007 in model 1 and -0.0169 in model 2 for the *starting physician* equation; $\beta_4 = -0.0693$ in model 3 vs. -0.0077 for model 1 and -0.0187 for model 2 for the *ending physician* equation). This result suggests that it is important to allow for correlation of the number of prescriptions written by each pair of physicians. We find the physicians' own lagged prescriptions to be significant but the cross-lags to be insignificant. This result shows that physicians have persistence in their own prescribing behavior (Bhatia & Krishnamurthi, 2006) but that there is no significant lag in the peer-to-peer effects.

Pooled sample: The number of prescriptions written by the *ending physician* has a negative significant effect on the *starting physician* and *vice versa*. There is a time trend in the data captured by the monthly fixed effects (eight and nine of which are significant in the *starting physician* and *ending physician* equations, respectively). There is also a similar trend in prescribing behavior over location, as captured by the number of prescriptions written by the other physicians in the same zip code. The coefficients of this variable are highly significant in all of the equations pointing to significant location specific shocks in the number of prescriptions written by the physicians. Hence, we try to control for time period and location-specific influences on prescribing behavior and find them to be strong and significant as in Nair et al. (2010). We model the effect of detailing and sampling by the sales

Table 3
Model comparison—pooled sample.

	Model 1 (OLS with physician fixed effects)	Model 2 (2SLS with instruments and physician fixed effects)	Model 3 (3SLS with instruments, physician fixed effects, correlated errors)
Time fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Instruments	No	Yes	Yes
Correlated error terms	No	No	Yes
No. of observations [e]	222,000	222,000	222,000
Cross-model correlation	0	0	0.1155
Dependent variable: Starting physician[a] prescriptions			
Starting physician detailing	0.0169*	0.0169*	0.0191*
Starting physician sampling	0.0001*	0.0001*	0.0001*
$z^{i}_{-sample,t}$ [c]	1.0750*	1.0783*	1.1843*
Ending physician prescription	**−0.0070***	**−0.0169***	**−0.0437***
Lagged *ending physician* prescription	0.0008	0.0022	0.0002
Lagged *starting physician* prescription	0.1449*	0.1449*	0.1448*
Network physicians'[d] prescription	0.0011	0.0011	−0.0543*
Adjusted R^2	7.17%		
Dependent variable: Ending physician[b] prescriptions			
Ending physician detailing	0.0113*	0.0113*	0.0123*
Ending physician sampling	0.0002*	0.0002*	0.0002*
$z^{j}_{-sample,t}$	1.1172*	1.1208*	1.1880*
Starting physician prescription	−0.0077*	−0.0187*	−0.0693*
Lagged *starting physician* prescription	0.0016	0.0032	0.0008
Lagged *ending physician* prescription	0.1380*	0.1381*	0.1380*
Network physicians' prescription	0.0008	0.0008	−0.0268*
Adjusted R^2	7.20%	7.21%	7.15%

* Two sided test: significant at $\alpha = 0.05$.
[a] *Starting physician* is the physician the patient/s move from.
[b] *Ending physician* is the physician the patient/s move to.
[c] Mean number of prescriptions of the other physicians who are in the same zip code as the physician *i* (and *j*) but not in the sample.
[d] Network physicians are all the other starting and ending physicians of the focal physician.
[e] There are a total of 9250 pairs of physicians identified based on patient movements, and each has 24 observations.

force of the pharmaceutical firm to the individual physician in all three models. The marketing activities of pharmaceutical firms directed at the physicians affect the physicians' prescribing behavior positively and significantly. The magnitude of the effect varies for the different physicians.

Next we present estimates for the various groups of patient movements in Michigan (Table 4) and in Texas and Georgia (Table 5). We find a significant effect of the marketing activities of the pharmaceutical firm (both detailing and sampling) on the number of prescriptions written by the *starting* and *ending physicians* in most cases, as has been described in the existing literature. We also find significant trends in time and location as described in the pooled sample discussed previously. We find the physicians' own lagged prescriptions to be significant, but the cross-lags are insignificant. This result shows that physicians have persistence in their own prescribing behavior (Bhatia & Krishnamurthi, 2006) but that there is no significant lag in the peer-to-peer effects. In our data, the number of prescriptions written is at the monthly level, suggesting that the peer effect occurs very soon after the patient movement. We also ran the model without the lagged physician prescriptions, and all of the main results were similar.

a) PCP–PCP: In our PCP survey, we find that every PCP mentions that they would never refer a patient to any other PCP (see Appendix A). This finding implies that all of the patient movements in this group are patient-generated and do not reflect any underlying physician network. These patient movements could be due to disgruntled patients, changes in insurance, and other patient idiosyncratic factors. We find a significant negative effect of the *starting* PCP on the *ending* PCP ($\beta_4 = -0.0925$, $p < 0.0001$) and *vice versa* ($\alpha_4 = -0.1112$, $p < 0.0001$). If most of these patient movements are due to disgruntled patients who are not happy with their current PCPs, we would expect the *ending* PCP to try a different treatment than did the *starting* PCP with whom the patient was not satisfied. In other words, the *ending* PCP learns what not to do from the *starting* PCP ('*observational learning*' as per Manski, 2000) and so we see a negative effect of the *starting* PCP's prescriptions on the *ending* PCP's prescriptions. Manski (2000) discusses observational learning wherein "observation of chosen actions may reveal private information". In this case, the prescriptions written by the *starting physician* for a patient are revealed to the *ending physician*. Here the observational learning leads to negative social influence in the sense that the *ending physician* learns what the *starting physician* did incorrectly because the patient was unhappy with the treatment received from the *starting physician*. The *ending* PCP's prescriptions also have a significant negative effect on the *starting* PCP's prescriptions. In this case, the effect could be due to *congestion* effects (Manski, 2000) because the *starting physician* loses patients to the *ending physician.*

b) PCP–SP and SP–PCP: In our estimation results, we find an asymmetric peer effect wherein the specialists' prescriptions influence the prescriptions of the PCP positively and significantly ($\alpha_4 = 0.2680$ for PCP–SP, $p < 0.0001$; $\beta_4 = 0.0998$ for SP–PCP, $p = 0.013$) but not *vice versa* ($\beta_4 = -0.0082$ for PCP–SP, $p = 0.506$; $\alpha_4 = -0.0168$ for SP–PCP, $p = 0.192$). This outcome is consistent with the opinion leader effect prediction and suggests that the opinion leader effect dominates all the other effects. Because we cannot exclude the possibility of patient-generated movement, which has an opposite effect, the positive asymmetric peer effect we identify here offers a lower-bound estimate of the opinion leader effect. We find this opinion leader effect to be strong and consistent in both the PCP–SP and SP–PCP groups in each of the three states we analyzed. Because the SP–PCP group does not contain the same physician pairs as the PCP–SP group, the size of the opinion leader effect may differ between the groups.

Table 4
Model 3 estimates by group for Michigan.

	PCP–SP	SP–SP	PCP–PCP	SP–PCP
Time period fixed effects	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes
Instruments	Yes	Yes	Yes	Yes
System weighted R^2	8.42%	5.58%	6.65%	8.12%
Cross-model correlation	−0.1491	−0.0562	0.2071	−0.0173
No. of observations	54,360	35,328	81,216	51,096
Dependent variable: Starting physician[a] *prescriptions*				
Starting physician detailing	0.0110	0.0328*	0.0130*	0.0283*
Starting physician sampling	−0.0001	0.0004*	0.0001*	0.0008*
$z^{i}_{-sample,t}$ [c]	1.5367*	0.7402*	1.1752*	1.0263*
Ending physician prescription	0.2680*	0.0064	−0.1112*	−0.0168
Lagged *ending physician* prescription	−0.0067	0.0118	−0.0022	0.0032
Lagged *starting physician* prescription	0.2195*	0.1499*	0.0979*	0.0627*
Network physicians [d] prescription	−0.1306*	0.0241*	−0.1040*	0.0137*
Dependent variable: Ending physician[b] *prescriptions*				
Ending physician detailing	0.0324*	0.0324*	0.0151*	−0.0049
Ending physician sampling	0.0011*	0.0009*	0.0001*	−0.0001
$z^{j}_{-sample,t}$	1.0273*	1.0694*	1.0893*	1.4966*
Starting physician prescription	−0.0082	0.0355	−0.0925*	0.0998*
Lagged *starting physician* prescription	−0.0003	0.0161	0.0015	−0.0153
Lagged *ending physician* prescription	0.1090*	0.0837*	0.1084*	0.2005*
Network physicians' prescription	0.0253*	0.0022	−0.0562*	−0.0676*

* Two sided test: significant at $\alpha = 0.05$.
[a] *Starting physician* is the physician the patient/s move from.
[b] *Ending physician* is the physician the patient/s move to.
[c] Mean number of prescriptions of the other physicians who are in the same zip code as the physician *i* (and *j*) but not in the sample.
[d] Network physicians are all the other starting and ending physicians of the focal physician.

c) SP–SP**:** Because these movements are a mixed case with some patient-generated movements and some physician-generated movements, the results are determined empirically by the size of the respective groups. We find the peer effects to be insignificant ($\alpha_4 = 0.0064$, $p = 0.8535$; $\beta_4 = 0.0355$, $p = 0.2184$).

The number of observations is the largest for the PCP–PCP movements (about 37% of the observations), so this group has the highest weight in the pooled sample. Hence, the pooled results are similar to the PCP–PCP case where the *starting physician*'s prescriptions affect the *ending physician*'s prescriptions significantly and

Table 5
Model 3 estimates by group for Georgia and Texas.

	Georgia				Texas			
	PCP–SP	SP–SP	PCP–PCP	SP–PCP	PCP–SP	SP–SP	PCP–PCP	SP–PCP
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
System weighted R^2	6.46%	3.24%	7.49%	6.49%	10.44%	4.66%	15.82%	11.89%
Cross-model correlation	−0.4057	−0.1103	0.2249	−0.4960	−0.1327	0.0468	0.0290	−0.1485
No. of observations	105,672	79,704	164,088	101,832	176,232	100,440	245,880	156,168
Dependent variable: Starting physician[a] *prescriptions*								
Starting physician detailing	0.0771*	0.0893*	0.0725*	0.0558*	0.0853*	0.0365*	0.0826*	0.0534*
Starting physician sampling	0.0011*	0.0012*	0.0009*	0.0008*	0.0009*	0.0023*	0.0011*	0.0014*
$z^{i}_{-sample,t}$ [c]	0.6119*	0.6619*	0.5262*	0.6491*	0.8146*	0.6817*	0.8006*	0.7238*
Ending physician prescription	0.9247*	0.0794*	−0.1144*	0.0007	0.2075*	−0.0198	−0.0174*	0.0009
Lagged *ending physician* prescription	−0.0056	0.0053	0.0022	−0.0006	0.0031	−0.0048	−0.0022	−0.0019
Lagged *starting physician* prescription	0.1696*	0.0370*	0.1344*	0.0573*	0.1847*	0.0967*	0.2023*	0.0904*
Network physicians[d] prescription	−0.0449*	−0.0078*	−0.0181*	−0.0063*	−0.0103*	0.0010	−0.0067*	0.0027*
Dependent variable: Ending physician[b] *prescriptions*								
Ending physician detailing	0.0613*	0.0867*	0.0690*	0.0734*	0.0581*	0.0462*	0.0769*	0.0895*
Ending physician sampling	0.0012*	0.0013*	0.0011*	0.0015*	0.0012*	0.0015*	0.0011*	0.0011*
$z^{j}_{-sample,t}$	0.6305*	0.8044*	0.4939*	0.5703*	0.8834*	0.9333*	0.8022*	0.8493*
Starting physician prescription	0.0070	0.0589	−0.1070*	1.3031*	−0.0015	−0.0366	−0.0245*	0.2246*
Lagged *starting physician* prescription	−0.0025	0.0040	0.0025	0.0008	0.0019	0.0020	0.0014	0.0004
Lagged *ending physician* prescription	0.0116*	0.0525*	0.1279*	0.1753*	0.0951*	0.0762*	0.1728*	0.1817*
Network physicians prescription	−0.0046*	0.0007	−0.0187*	−0.0802*	0.0003	0.0007	−0.0086*	0.0028*

* Two sided test: significant at $\alpha = 0.05$.
[a] *Starting physician* is the physician the patient/s move from.
[b] *Ending physician* is the physician the patient/s move to.
[c] Mean number of prescriptions of the other physicians who are in the same zip code as the physician i (and j) but not in the sample.
[d] Network physicians are all the other starting and ending physicians of the focal physician.

negatively and *vice versa*. This result suggests that it is important to separate different patient movements when we estimate physician peer effects.

In Georgia and Texas, we find similar results for the PCP–SP group (and the SP–PCP group) with an asymmetric effect of the specialist's prescriptions on the PCP's prescriptions. We find the opinion leader effect in the PCP–SP case in Texas ($\alpha_4=0.2075$ for PCP–SP; $\beta_4=0.2246$ for SP–PCP) and in Georgia ($\alpha_4=0.9247$ for PCP–SP; $\beta_4=1.3031$ for SP–PCP). The results for the PCP–PCP case were also similar to those in Michigan, with the *starting* PCP's prescriptions having a negative effect on the *ending* PCP's prescriptions and *vice versa*. For the SP–SP group, the physicians had no significant effect on each other's prescriptions in Texas, while in Georgia, we find an opinion leader effect. To combine the evidence from all three states (Michigan, Georgia and Texas), we conduct a meta-analysis on the peer-to-peer effects using the method of adding weighted Z's (Deleersnyder, Geyskens, Gielens, & Dekimpe, 2002; Rosenthal, 1991). As shown in Table 6, the prescriptions of specialists have a significant positive influence on the prescriptions of PCPs ($p<0.001$) and not the other way around. Primary care providers have a significant negative influence on each other's monthly prescriptions ($p<0.001$), whereas specialists have no significant influence on each other's prescriptions.

In summary, we find two different peer effects based on patient movement data. The survey results imply that patient movement between PCPs is generated by patients. For this type of movement, we find significant negative effects of *starting physicians* on *ending physicians* and *vice versa*. We believe this result is mainly due to the *observational learning* effect and *congestion* effect. Patient movement between PCPs and specialists and back could be generated by the patient or the physician. If the movements are mostly generated by patients, then we should expect to see a similar effect as with movements between PCPs. However, we observe a totally different effect: the *specialists* affect the *PCPs* positively but not *vice versa*. This result is consistent with the opinion leader effect where the ending physician influences the starting physician. This result suggests that such movements are mostly physician referrals and reflect the physician network. The SP–SP case is a mixed case with both kinds of movements.

Robustness checks: Various sensitivity tests have been performed to test the robustness of our results. First, we use the market share of the focal drug, conditional on prescription, as the dependent variable in our model (as shown in Table 7). The share model captures the changes in prescriptions across drugs and offers a clean test of the peer effects. The peer effects from the share model are found to be consistent with those from the main model.

Second, we check the results for the PCP–SP (and the SP–PCP) using a cutoff of more than three patient movements between physicians to make sure these are physician-generated movements. We find the results to be even stronger and to have the same asymmetry in peer effects.

Third, we check the robustness of our results by varying the way in which we control for the prescriptions of other network physicians.

Table 6
Rosenthal test of the peer effects: MI, GA and TX combined: method of adding weighted Zs.

	PCP–SP	SP–SP	PCP–PCP	SP–PCP
Ending physician [b]'s effect on *starting physician* [a]	19.4437*	1.1203	−9.3877*	−0.2471
Starting physician's effect on *ending physician*	0.0051	0.1097	−10.1920*	20.2838*

Note: Reported values are the z-values.
*One-sided test: p-value<0.001.
[a] *Starting physician* is the physician the patient/s move from.
[b] *Ending physician* is the physician the patient/s move to.

Table 7
Model 3 estimates by group for Michigan with market share as the dependent variable and lagged effects.

	PCP–SP	SP–SP	PCP–PCP	SP–PCP
Time period fixed effects	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes
Instruments	Yes	Yes	Yes	Yes
System weighted R^2	0.66%	1.71%	0.57%	0.72%
Cross-model correlation	−0.2075	−0.0600	0.2367	−0.0235
A. Dependent variable: Starting physician[a] *market share*				
Starting physician detailing	0.0001	0.0032*	0.0146*	0.0312*
Starting physician sampling	0.0000*	0.0005*	0.0002*	0.0008*
$s^i_{-sample,t}$ [c]	0.7934*	0.6114*	0.7100*	0.6953*
Ending physician market share	0.2015*	0.1043	−0.0982*	0.0373
Lagged *ending physician* market share	0.0312	0.0471	−0.0129	0.0130
Lagged *starting physician* market share	0.1831*	0.1733*	0.1137*	0.0822*
Network physicians [d] market share	−0.0891*	0.0083*	−0.0156	−0.0040
B. Dependent variable: Ending physician[b] *market share*				
Ending physician detailing	0.0075*	0.0042*	0.0124*	−0.0002
Ending physician sampling	0.0011*	0.0009*	0.0003*	0.0003*
$s^j_{-sample,t}$	0.5933*	0.5521*	0.6299*	0.5770*
Starting physician market share	0.0543	0.1249	−0.0906*	0.1301*
Lagged *starting physician* market share	0.0001	0.0213	0.0021	0.0008
Lagged *ending physician* market share	0.0921*	0.0899*	0.0919*	0.1665*
Network physicians' market share	0.0442*	0.0203*	−0.0339*	−0.0334*

* Two sided test: significant at $\alpha=0.05$.
[a] *Starting physician* is the physician the patient/s move from.
[b] *Ending physician* is the physician the patient/s move to.
[c] Mean number of prescriptions of the other physicians who are in the same zip code as the physician i (and j) but not in the sample.
[d] Network physicians are all the other starting and the ending physicians of the focal physician.

We obtain similar results using the average number of prescriptions written by other physicians weighted for the number of patient movements.

6. Managerial implications

To evaluate the managerial implications of our influence estimates on the targeting decisions made by the pharmaceutical firm, we estimate the social multipliers for the involved physicians in the

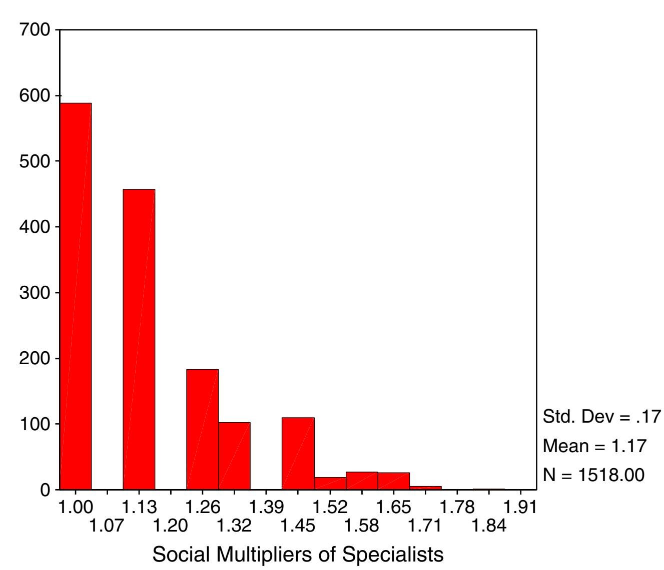

Fig. 1. Histogram of specialists' social multipliers.

Michigan sample. The incremental detailing or sampling to an opinion leader has two effects. The direct effect is an increase in the number of prescriptions issued by the opinion leader. The indirect effect is that the increase in the opinion leader's prescriptions increases the other connected physicians' prescriptions through social influence. We estimate the social multiplier accounting for the indirect (social) effect.

We calculate the social multiplier at the individual physician level to identify the opinion leaders for the Michigan sample. There are 4355 physicians in the sample. Because we find that only specialists have opinion leader effects on PCPs, we calculate the opinion leader effect for a specialist if s/he receives at least one patient from PCPs. Because of the imperfect classification of the patient-generated and physician-generated movements in the PCP–SP (and the SP–PCP) case, the opinion leader effect we obtained is a lower-bound estimate. Therefore, the social multiplier estimate is also a conservative estimate. Based on our model estimates in Table 4, the average direct effect of detailing of the focal drug on these specialists is 0.0304 (0.0324 for specialists in the PCP–SP case and 0.0283 for specialists in the SP–PCP case). In the aggregate data for the category, we find that one new prescription generates on average two renewals and that the revenue from one additional dose of a combination drug is about \$50.00. Thus, the incremental revenue from an additional prescription is about \$150.00. Given this, the incremental revenue from one additional detail in the category is \$4.56 (= 0.0304 150). The revenue is further increased due to the opinion leader effect. From Table 4, we know that one additional prescription from each *specialist* leads to an average of 0.1839 additional prescriptions by a PCP (0.268 in the PCP–SP case and 0.0998 in the SP–PCP case). Therefore, the incremental revenue due to the social influence on a PCP is 0.0304 150 0.1839. Thus, the total social opinion leader effect of a specialist is M = 0.0304 150 0.1839 n_PCP, where n_PCP is the number of PCPs who send (or receive) patients to (from) the specialist. Following Nair et al. (2010), we calculate the social multiplier as 1 plus the percentage of incremental revenue due to the indirect (social) effect, i.e., 1 + M/(M + 0.0304 150). In Fig. 1, we show the histogram of the social multiplier for all specialists. Among 1518 specialists, 930 specialists have a social multiplier greater than 1 and are identified as opinion leaders. The average social multiplier of these opinion leaders is 1.27 (ranging from 1.16 to 1.83), which is significantly greater than 1 (p-value < 0.001). In other words, we find that the opinion leader effect provides an average increase of 27% in the Return on investment (ROI) due to the detailing of these opinion leaders. Note that our social multiplier estimates are higher than in Nair et al. (2010). Their social multiplier estimates range from 1.05 to 1.35. Using movement data gives us higher social multiplier estimates than using self report survey data because the two types of data reveal different levels of opinion leader effect. In the survey, all physicians are asked to nominate physicians who influence them. The survey does not reveal all of the physicians influenced by a particular physician but a subset of them. Therefore, using survey data most likely underestimates the true social influence effect.

To identify characteristics of opinion leaders, we run a regression of the social multipliers on specialty categories, the number of physicians in each zip code, and the category prescription deciles. We find that the two focal specialties in this category, cardiologists and nephrologists, have significantly higher social multipliers than the other specialists (0.160, $p<0.0001$ for cardiologists; 0.053, $p = 0.0002$ for nephrologists) and that cardiologists have the highest social multipliers. The number of physicians in the zip code has no effect on the social multiplier, while the category prescription decile has a positive and significant effect (0.023, $p<0.0001$) on the social multiplier. This result implies that specialists who prescribe more in the category are more likely to be opinion leaders.

Our results provide useful insights for pharmaceutical firms to allocate resources more effectively. First, as Glaeser, Sacerdote, and Scheinkman (2003) point out, the presence of social interactions implies the existence of a social multiplier where aggregate relationships will overstate individual elasticities for marketing activities by pharmaceutical firms. Hence, pharmaceutical firms need to estimate this social multiplier to optimally allocate marketing resources across physicians. Second, as suggested by our results, the firms should take both physicians' deciles and social multipliers into account when allocating marketing resources. Because the specialists for this therapeutic area prescribe less frequently than the primary care physicians (see Table 2 and the discussion in Section 3) and are therefore detailed less by pharmaceutical firms, it is very important to take into account the social multiplier of the specialists so that they do not under-detail these physicians.

7. Conclusion

This paper models the peer-to-peer effect among physicians in the local region using patient movement data combined with physician prescription and targeted marketing data. We categorize the patient movements as patient-generated and mostly physician-generated based on information from a physician survey. We find that the groups we categorize as having mostly physician-generated patient movements (SP–PCP or PCP–SP) reflect the physician network so that specialists' prescriptions have the opinion leader effect on the PCPs' prescriptions. The patient-generated movements (PCP–PCP) reveal private information about the *starting physician* to the *ending physician*, leading to *observational learning* by the *ending physician*, whose prescriptions are negatively influenced by the *starting physician*'s prescriptions. The *starting physician*'s prescriptions are also negatively influenced by the *ending physician* due to *congestion* effect.

These findings have several important management implications for targeted marketing by pharmaceutical firms. First, the detailing and sampling responsiveness estimates are biased in the presence of social interactions, (Blume, 2003) and hence, the allocation of marketing resources based on those estimates is not optimal if we do not adjust for the social multipliers. Second, specialists who are the opinion leaders are lower prescribers compared with PCPs and consequently are detailed and sampled less by pharmaceutical firms; therefore, increasing detailing of and sampling to the specialists would increase the number of prescriptions written by the other physicians through social influence. Third, we find higher-prescribing specialists and those belonging to focal specialties who deal more with the disease category (such as cardiologists and nephrologists, in this case) to be more likely to be opinion leaders. These results imply that when designing optimal detailing and sampling strategies, pharmaceutical firms should take into account each physician's social multiplier along with the physician's prescription deciles.

This research has several limitations. The main limitation, in our view, is that we do not observe actual physician interactions or patient referrals between physicians; we only observe patient movements between physicians. While we try to utilize the institutional features to identify physician-generated patient movements, direct referral information would be more useful for identifying physician networks. The second limitation is that we do not observe the insurance status of each patient movement, which would enable us to adjust for insurance effects on the network. Lastly, this research does not look at the demographic profile of the patients, which could have an influence on the physician network.

Future research could focus on mapping out the influence networks of these physicians, adjusting for whether the physicians are 'in-network' or '*out-of-network*' depending on the patients' insurance type. Additionally, the patient profile of a given physician could impact the patient movement to and from that physician. For example, the profile of patients who would be sent to a specialist may differ from that of patients sent to a PCP based on their age, gender, race, or concomitant diseases, for example. It may also be advantageous to empirically test how the self-reported physician opinion leaders differ from those identified by behavioral data.

In conclusion, we develop a methodology to identify peer-to-peer effects using patient movement data, which has important implications for targeted marketing by pharmaceutical firms. We find that physician peer effects depend on the nature of patient movements. In cases of mostly physician-generated patient movements, we find that the influence on prescriptions is asymmetric and is in the opposite direction to the effect of patient-generated movements. We calculate the social multiplier for these opinion leaders, which adds to the existing literature a deeper understanding of patient movements and physician peer effects. Our methodology can also be applied to other situations where we observe interactions among individuals (for example, friends leaving comments on each other's web page) and we want to estimate the peer effect on consumption behavior.

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Appendix A. Physician interviews and survey

We interviewed a convenience sample of seven primary care physicians and five specialists to better understand the process of patient movements and to gauge the relationship between patient movements and physician networks. We followed these in-depth interviews with a quantitative survey of 38 physicians, 20 of whom were specialists. Please refer to Appendix B for the survey questionnaire.

The primary care physicians routinely referred patients to specialists when their care required it. They cited the reasons for their choice of specialists to be based on expertise, interests, personality, reputation, and relationship with group practice/clinics. This result implies that at least some of the patient movements from the primary care physicians to specialists are physician-generated due to referrals from the primary care physicians. All primary care physicians unanimously stated that they would never refer any patient to another primary care physician because that would be equivalent to losing the patient to a competitor. This finding implies that the movements between primary care physicians are patient-generated. The primary care physicians learn from the specialist to whom they send patients to in two ways. First, they learn how to treat that particular patient whose problem they were not able to solve. Second, they learn how to treat the same problem in future patients.

The specialists usually work together with specialists in different fields to provide treatment to the patient. For example, a cardiologist will work closely with a nephrologist to make sure the patient's kidneys are fine and perhaps with an endocrinologist because there is a high chance that the patient has diabetes if he has a heart problem. Therefore, the specialists will refer patients to physicians of different specialties with whom they work. Specialists do not usually refer patients to specialists within the same specialty unless the referred specialist has a specific sub-specialty. Only rarely do specialists refer patients to specialists in the same field for second opinions. In our sample, all specialists referred patients to physicians with specialties different from their own, and 26% referred patients to physicians with the same specialty occasionally.

All of the surveyed primary care physicians unanimously agreed that they learn from the specialists to whom they refer patients. They have a clear feedback mechanism wherein the specialist writes a note back to the referring physician informing him/her of the treatment he has recommended to the patient, including his diagnosis, any prescriptions he has started the patient on, any dietary changes, any tests performed or recommended, and whether he will see the patient again and when. The surveyed primary care physicians stated that they would not refer any patients to specialists who did not send them this progress note, thus ensuring an enforcement mechanism for getting feedback from the specialist. The feedback mechanism is usually by a document in the mail, though with the rise of electronic medical records (especially for physicians working in the same hospital/group practice), it is sometimes electronic or oral. In our sample, 68% of physicians stated receiving document feedback, 63% oral feedback, and 42% electronic feedback at some point. The timing of the feedback depends on the nature of the feedback. The electronic and oral feedback is received within a week, while mail feedback typically takes one to two weeks (because these physicians are all local). In our sample, 16% stated the timing of feedback to be within one week, 47% between one to two weeks, and 37% between three to four weeks; none of the feedbacks took longer than one month to receive.

Appendix B. Physician survey

My name is XXX and I am a professor of marketing at XXX University. My research is predominantly on physician decision making and physician networks. I need the following information for a physician network study. Please state your specialty and mark an X next to the answer. Please feel free to write any comments on the patient referral process between physicians. All survey participants will remain anonymous.

Your specialty:_________________

Q1. Would you refer a patient to a physician with the same specialty as yours?

YES ______________ NO ______________

Comments:____

Q2. Would you refer a patient to a physician with a different specialty from yours?

YES ______________ NO ______________

Comments:____

Q3. When you refer patients to another physician, how and when do you get feedback from the physician?

Nature of feedback:

Document ___________ Oral ____________ Electronic_____________

Timing of feedback:

<1 week______ 1–2 weeks______ 3–4 weeks______ >1 month_____

Thank you very much for your help.

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