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

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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

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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.