Knowledge Acquisition and Sharing: How Much Do Colleagues Matter?

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Abstract : Knowledge transfer between workers in an organization is challenging to manage. Workers learn about innovations from their colleagues and from other workers outside the firm's organisational boundary, but behavioural factors may favour one source of learning over the other. Which source is likely to prove superior, when? Drawing on theories of social contagion, knowledge sharing and organisational learning, we develop a dynamic individual-worker level model to answer this question. We test our proposed model in the context of physician's prescription of a new technology using actual prescription data. We find that, on average, physicians learn about the technology from their internal colleagues more than from their external rivals (i.e. those who work in competing practices that are located in the region of their practice). However, both physicians with the greatest cumulative knowledge of the new technology and those with the least show the opposite pattern, i.e., they are influenced less by their internal colleagues than by external rivals.

Keywords: *Knowledge sharing; social contagion; worker learning; intra organisational learning; in-group threat; innovation*

Introduction

Consider the following scenario: An organisation has adopted a new technology, one that is presumably better than the older technology it replaces. The organisation encourages its employees to use the new technology instead of the old one. Some employees are uncertain about the quality of the new technology; faced with high learning costs, they continue to use the older technology. Other employees with lower learning costs learn about the technology quickly and with experience, gain more confidence in using the new technology. However, even workers who have higher learning costs can interact with and learn from those who have been using the technology. From an organisational perspective, such transfer of work-related knowledge between workers is critical to achieving and maintaining high levels of individual worker performance and organisational efficiency (Morgan et al. 2003, Argote, McEvily and Reagans 2003, Robson et al. 2008). It is essential that employees share knowledge about the technology with each other to transform individual employee knowledge into organisational learning (Albers et al. 2013, Siemsen et al. 2009). An employee who shares her knowledge also stands to gain from sharing via important feedback questions, modifications and an understanding of "what-if" scenarios, which increase the value of the knowledge that the experienced worker possesses (Friesl, 2012).

However, promoting knowledge creation and sharing between employees within an organisation is challenging for managers (Kogut and Zander 1992, Albers et al. 2013). Social contagion, wherein the behaviour of a focal actor varies with the behaviour of the other individuals with whom the focal actor interacts (Manski 2000), plays an important role in knowledge transfer and consequently, in the adoption of innovations, especially in knowledge intensive markets. Because products in these markets are often characterized by high uncertainty with regards to their quality (von Hippel 1986) social contagion is very effective in influencing adoption since it is viewed as an unbiased source of information (Rogers 1995). Social contagion would suggest that a focal employee is likely to learn about the new technology from other fellow colleagues in the same organisation and from other individuals who work in competing organisations in the geographical area (with whom the focal employee is likely to interact).

Extant research in the management (Shah 1998) and organisational learning literature (e.g. Menon et al. 2006, Hotho et al. 2012) has acknowledged the possibility of behavioural factors acting as barriers to workers learning from each other. Even though colleagues' knowledge can be easily accessible, employees may not learn from them; research in organisational learning has established that a worker can feel that learning from a fellow worker in the same organisation may be equivalent to acknowledging the superiority of the latter, and as a result, may fear a downgrade of status within the organisation (Shah 1998; Schimel et al. 2001). Prior research has also established that individuals are more likely to learn from those who work in other organisations, because it may not carry the taint of 'mimicking' one's internal colleagues (Menon et al. 2006); more strongly, the act of learning from others outside of one's own organisation can be perceived as out-of-the-box thinking and being vigilant (Ancona et al. 2002).

Although extant research in the management literature has documented the challenges in employee knowledge sharing, there are important questions that remain unanswered. No study has examined how workers learn about an innovation from other workers within the organisation (internal colleagues) versus from workers in competing organisations (external rivals), in the field. Furthermore, no study has investigated the transfer of new knowledge between workers, while simultaneously accounting for worker's self-learning via experience (direct experience). The few studies that do look at both internal and external factors use laboratory based experimental data or surveys (e.g., Menon et al. 2006, Aalbers et al. 2013). This raises concerns of both limited external validity and self-report (e.g., social desirability) bias. By contrast we use actual choice data to study all three forms of learning – external, internal, and self. And finally, no study has systematically examined the behavioural factors that can make workers seek out knowledge more from one source versus another, an objective which lies at the core of our work.

We address our research questions with an empirical analysis of a panel data set of specialist physicians' prescriptions of a new medical technology. The context is appropriate because it features all three forms of learning in a knowledge-intensive environment with the kind of uncertainty that makes the seeking of information imperative. A physician who is aware of a new medical technology may be hesitant in prescribing the product to her patients due to the uncertainty associated with the quality of the technology.[1] However, the physician can learn about the quality of the new product directly from other physicians via interpersonal communication and informal knowledge sharing (Haug 1997; Keating et al. 2007). There could be two sources of such knowledge - those physicians who work in the same practice (internal colleagues), and those physicians who work in the region of her practice, and with whom she is likely to interact (external rivals).[2] In addition, the physician certainly learns about the new technology from her own direct experience with the product, i.e., from direct observation of, and feedback from, patients.

We leverage a unique dataset to create individual physician-specific measures of knowledge transfer from internal colleagues and external rivals. We estimate our proposed econometric model on physicians' prescription behaviour of a new test using Monte Carlo simulation methods.

Our results suggest that physicians learn about the innovation from both internal colleagues and external rivals and that on average, internal colleagues have a marginally greater effect than external rival. We control for self-learning and thus this knowledge gain is over and above what the physician learns via experience. Physicians with greater knowledge are influenced less by internal colleagues than their external rivals while physicians who have minimal experience with the product depend more on external rivals for knowledge thus, supporting status and rivalry in knowledge transfer. Based on our results, we offer implications for managers to strategically design knowledge transfer within an organisation.

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[1] Even though new drugs and other pharmaceutical products are approved by regulatory authorities (e.g., the FDA in the US), the actual quality of the products is not known for some time (CDER 2000).

[2] To the extent that specialist physicians in a practice compete against other practices in the geographical area, we believe that the terminology is appropriate.

The remainder of the manuscript is organized as follows. In Section 2, we discuss the background literature on knowledge transfer between employees and the effects of social contagion. In Section 3, we explain the data and the industry background. In Section 4, we present our proposed model, discuss important specification issues and outline the estimation procedure. We present estimation results in Section 5 and conclude with a discussion of results, implications and directions for future research.

Literature Review

Organisational learning research has recognized that knowledge is a valuable resource for a firm as it represents intangible assets that cannot be imitated easily by competing firms (Grant 1996). As for sources of such knowledge, extant research has demonstrated that workers are more likely to turn to other workers for knowledge. Allen (1997) reported that engineers and scientists were approximately five time more likely to acquire information from a person than from an impersonal source such as a database (Levin and Cross 2004). In the particular context of physicians, studies in the medical literature have documented that staying abreast of current knowledge is among the most difficult challenges physicians face (Laine and Weinberg 1999). Most physicians find it difficult to get adequate information sources like journals, review articles, and clinical guidelines (Wyatt 1991, Pauker et al. 1976, Smith 1996) and often rely on a trustworthy and easily accessible source of information i.e., other physicians (Laine and Weinberg 1999).

However there is also evidence that employees often do not want to share knowledge with their co-workers; this may be to avoid a decrease in self-valuation or distinctiveness within the organisation (Menon et al. 2006), to maintain psychological safety in sharing (Siemsen et al. 2009, Shah 1998) and to maintain a positive social identity within the organisation (Menon and Pfeffer 2003), among other reasons.

However, even if the desire to seek knowledge from one's co-workers is present, there may be the bigger issue that the co-workers themselves do not possess the knowledge that is sought; one may have to rely on individuals and links outside the organisation in order to acquire new knowledge (Anand et al. 2002). Social network theory and tie strength arguments (Granovetter 1973, Aalbers et al.2014, Hansen 2002) suggest that although a focal actor may not have frequent interaction with individuals outside the organisation, the knowledge gained from such individuals can be novel and more useful than knowledge from those within. At the dyadic level, weak ties that are distant and characterized by infrequent interaction can serve as sources of novel knowledge when compared to strong ties. Further, the behavioural factors enumerated above (rivalry, status), may lead the employee to prefer seeking information from outside the organisation.

Knowledge transfer between individuals is closely tied to the concept of social contagion. The social contagion literature (Manski 2000, Burt 1987) suggests that a decision maker's perception of an innovation is determined by his exposure to the knowledge, attitudes, and behaviour of the users of the innovation (Van Bulte and Lilien 2001). One of the reasons why social contagion is very effective in individuals' learning of a new product is that it is unbiased to the extent that its origin is independent from the firm marketing the product. This argument is especially applicable in our context of physicians' prescription of a new product or technology. Although firms in the medical and pharmaceutical industry have an army of sales representatives to promote their product to physicians, sales representatives are neither experts nor viewed as objective or even accurate (Connelly et al. 1990). On the other hand, physicians have a reliable and easily accessible source of information in the form of other physicians (Laine and Weinberg 1999).

Informational exchange via social contagion is built on the premise that people who live closer to each other interact with each other more often and can influence each other's behaviour and attitudes (homophily). Geographic proximity is the most basic source of homophily that connects people (McPherson et al. 2001), and the distance between any two people serves as a proxy for their degree of influence on each other (Strang and Tuma 1993), and the extent of informational transfer between them. Geographic proximity is also an important factor that influences the closeness of a relationship between two people, as determined by the multiplexity and frequency of contact between them (McPherson et al. 2001).

Research Context and Data Description

The research is in the context of an innovative product (a laboratory based test) developed by a small start-up firm for a therapeutic condition.[3] More than a million cases are diagnosed each year with this condition, and the number of patients in the US has been increasing. The disorder requires a quick diagnosis and patients need monitoring and regular follow up visits. This test, developed by specialists in the field, currently enjoys patent protection. The test helps physicians assess their patients' current condition, and also helps them prescribe guidelines to patients in order to prevent recurrence.

[3] We are unable to reveal the name of the firm and the product due to a confidentiality agreement between us and the firm.

Our panel dataset tracks the prescription behaviour of 536 physicians after their adoption of the product and spans twelve quarters since the introduction of the product. Since we observe the prescription behaviour of physicians from first adoption, we do not have a left-censoring issue in the data, and thus the knowledge accumulated by these physicians before our study time period is not an issue. The distribution of the number of physicians who adopted the technology and the number of times the product was prescribed by the panel of physicians over the study time period is given in Table 1.

Table 1: Distribution of the Adoption and Prescription Rate of the Physicians

Quarter	**Number of physicians who adopted in the quarter**	**Total number of prescriptions written in the quarter**
1	28	379
2	42	703
3	48	738
4	50	924
5	55	982
6	55	1118
7	59	981
8	33	1109
9	46	1197
10	44	1241
11	30	1187
12	46	1377

In total, we have 4180 physician-quarters observations with a mean prescription rate of 2.86 and standard deviation of 4.29. We also have information on the practice, that each of the physicians works for, and the addresses of the practices. Physicians' prescription behaviour is used to operationalize social contagion between focal physician and internal colleagues and external rivals, allowing us to infer knowledge transfer between them.

The number of years the physicians have been practicing since graduation (tenure), and whether or not the practice is a teaching hospital (i.e. affiliated with a university) are used as control variables in the econometric model.

We note that the firm in our context (being a start-up firm), was resource constrained and did not market its product through advertising or sales calls. For the reasons discussed in the earlier section on modelling contagion, this unique feature is important to our context. Since we are modelling knowledge transfer via their actual prescription behaviour, and because the advertising of a product can also influence physicians' prescription behaviour, it is important to control for the marketing efforts undertaken by the firm that markets the technology. In our case, there were no marketing communication efforts (e.g. advertising, sales call etc.) controlled by the firm. This feature helps us to better capture the effect of social contagion from internal rivals and external colleagues on physicians' prescription behaviour. Since all the physicians are specialists in the particular therapeutic category we capture knowledge transfer between "peers", thereby eliminating the possibilities of an asymmetric influence of specialist physicians onto general physicians and vice-versa.

Methods

Modelling Social Contagion

Contagion measured via behavioural data is not observed but inferred (Manski 2000). As researchers, we do not actually observe the informational exchange between physicians, but infer it from the prescription behaviour of physicians. Therefore, we build on the extant literature in economics that has modelled contagion using behavioural data (for example Goolsbee and Klenow 2002). Let us first explain the challenges in modelling contagion using behavioural data and how we overcome these limitations by using appropriate features of our unique data and econometric specifications, which will help us identify social contagion between physicians.

Assume that an econometrician finds that physicians' prescription behaviour is influenced by the prescription behaviour of their internal colleagues and external rivals. In order for the researcher to attribute this effect to social contagion or informational exchange, the researcher should rule out other factors besides contagion that might make the prescription behaviour of colleagues or geographic neighbours look similar. Manski (1993, 2000) identifies three types of peer effects: endogenous effects, contextual effects and correlated effects. Our substantive interest is in the endogenous effect, which in our context, would exist, if ceteris paribus, a physician's prescription behaviour varies with the prescription behaviour of his colleagues and neighbours. Contextual or exogenous effects can arise due to the particular context or geographic region that is being studied. Examples where actions of an individual depend on such exogenous characteristics may include the geographic region that can make the region an "outlier". Correlated effects arise when unobserved institutional factors make the physicians behave in similar fashion. Since these factors are unobserved, an econometrician who does not control for such factors will wrongly attribute the choice behaviour to social contagion. In our context, examples of unobserved institutional factors can be exogenous demand shocks, such as an increase in the price of a competing product that could make physicians prescribe the particular product. It would seem to a researcher that these physicians are behaving similarly due to contagion, when in fact, their behaviour is driven by the unobserved factors.

There are a few more issues to keep in mind in order to estimate the effect of contagion on physicians' prescription behaviour. Among the extant studies that have examined social contagion, the study of Medical Innovation by Coleman, Katz and Menzel (1966) is one of the first. Set in the context of physicians' adoption of a new antibiotic, the study is credited with establishing that the diffusion of innovation is driven by social contagion (Rogers 1995). However, in a later study, Van den Bulte and Lilien (2001), using the same dataset, demonstrate that once marketing efforts, such as advertising, are controlled for, the effect of social contagion disappears. This study highlights the importance of accounting for firms' marketing efforts when modelling social contagion. Lastly, models that rely on behavioural data use the mean behaviour (prescription behaviour in our case) of the group in order to operationalize the contagion variable. However, an identification problem, also referred to as the reflection problem (Manski 1993), arises if one cannot distinguish whether an individual physician's prescription behaviour affects the group's prescription behaviour, or if the group's prescription behaviour actually affects an individual physician's prescription behaviour. A solution to this problem is to leverage the dynamics present in the data, if available, and to test if individual behaviour varies with the lagged instead of the contemporaneous values of the group mean behaviour (Manski 2000).

Leveraging a unique dataset of physicians' prescription behaviour that we describe next, and by using adequate econometric specifications, we account for all of the issues mentioned above. To avoid the issue of contextual effects, we focus on a number of geographic regions from 31 states in the US. The mix of the regions from the different parts of the US will help make sure that contagion effect, if found, is not due to a specific geographic region. With respect to the correlated unobservable factors, we account for them by incorporating appropriate time specific fixed effects in our formulation.

We follow the solution prescribed by Manski (2000) to get around the reflection problem. In other words, we leverage the dynamics present in the data and test if individual consumer choice behaviour varies with lagged instead of contemporaneous values of the group mean choice behaviour. Finally, we also control for physicians' unobserved heterogeneity in their intrinsic prescription rate by adopting a random coefficient formulation. Doing so and accounting for all the challenges discussed above would present convincing evidence of social contagion and knowledge transfer across physicians.

Measures of Social Contagion

Prior research on social contagion in the context of consumers' adoption of an innovation (e.g. Van den Bulte and Lilien 2001; Goolsbee and Klenow 2002) have operationalized social contagion on a focal agent (at time t) by the behaviour of number of other agents in the previous time period (at time t-1). Following this precedent, we operationalize social contagion due to internal colleagues and external rivals for physician i in time t by the number of prescriptions written by the physician i's internal colleagues and external rivals in time t-1 respectively. The social contagion due to colleagues is relatively straightforward and is equal to the number of prescriptions of the product that is written by all of the physicians who work in the same practice as physician i. For calculating the contagion due to external rivals, we need to define the geographical area based on where external rivals work with whom the focal physician is likely to interact. We use a radius of 20 miles to first define what makes a "neighbourhood", and then we operationalize contagion by the number of prescriptions of the product written by those physicians who work in a 20 miles radius of physician i's practice. Using a commercial geocoding software, and from the zip code information of physicians' practice, we obtained the latitude and longitude of the physicians' practice location.

We then used this to calculate the distance between the physicians.[4] We picked the radius of 20 miles as this is consistent with what would typically be considered a "neighbour". Recent studies (for e.g. Manchanda, Xie and Youn 2008; Janakiraman and Niraj 2011)[5] have used similar radius to operationalize contagion measures.

Finally, we also use a set of control variables in our proposed econometric model. These include the physician's tenure, a physician's affiliation with a university and dummy variables for the different time periods.

Econometric Model Formulation and Estimation

In this subsection, we explain the model that we develop to estimate the effects of contagion from internal colleagues (professional colleagues) and external rivals (professional neighbours) on their prescription behaviour. Recall that the dependent variable is the number of times a physician i (i=1…I) prescribed the product in

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[4] Let the latitude and longitude of location X be (a, b) and the latitude and longitude of the location Y be (c, d), all of which are converted into radians: degree/57.29577951. Given that the radius of the earth is 6,652 km, we calculate the distance between X and Y as follows: If a = c and b = d, distance (in km) =0. If sin(a)sin(c) + cos(a)cos(c)cos(b-d) > 1, then distance (in km)= 6652; else, distance (in km) = 6652*arcos[sin(a)sin(c)+cos(a)cos(c)cos(b-d)].

[5] We performed sensitivity analyses with ± 25% of this radius and found our results to be the same substantively.

time period t (t=1…T). Let the number of prescriptions written by physician i in time period (quarter) t, conditional on having adopted the technology be denoted as y_{it}. Since this number is discrete and non-negative, consistent with prior literature, we assume that yit follows a Poisson distribution with a mean rate λit, (Hausman, Hall and Griliches 1984), as presented in Equation 1:

$$\Pr(Y_{it} = y_{it} \mid \lambda_{it}) = \frac{\lambda_{it}^{\,y_{it}} e^{-\lambda_{it}}}{y_{it}!}. \tag{1}$$

We model the mean rate λit as an exponential function of the contagion variables and a set of control variables (Hausman, Hall and Griliches1984). Accordingly, we express λit as follows:

$$\begin{aligned}\lambda_{it} = \exp(&\gamma_{0_i} + \gamma_1 \text{Knowledge}_{it} + \gamma_2 \text{Internal Colleagues\_Contagion}_{it} + \gamma_3 \text{External Rivals\_Contagion}_{it} + \\ &\text{Knowledge}_{it}(\gamma_4 \text{Internal Colleagues\_Contagion}_{it} + \gamma_5 \text{External Rivals\_Contagion}_{it}) \\ &+ \gamma_6 I_{it}^{\text{Minimum}} \text{Internal Colleagues\_Contagion}_{it} + \gamma_7 I_{it}^{\text{Minimum}} \text{External Rivals\_Contagion}_{it} \\ &+ \gamma_8 \text{Tenure}_i + \gamma_9 \text{University}_i + \sum_{k=10}^{21} \gamma_k \text{Time})\end{aligned} \tag{2}$$

In Equation 2, Knowledgeit is the knowledge (due to self-learning) about the new technology that physician i has at time t (as measured by the cumulative number of prescriptions written by the physician i until time t), Internal Colleagues_ Contagionit and External Rivals_Contagionit denotes contagion from internal colleagues and external rivals (as explained in the above subsection),

$I^{Minimum}$ is an indicator variable that is equal to 1 if the physician i at the previous time period (time t-1) had the least experience with the product across all physicians in the physician's practice. The control variable nclude the physician's professional experience (Tenurei), the physician's affiliation to a university (Universityi) and dummy variables for the different time periods (Time). The operationalization of the variables are in in Table 2 and the descriptive statistics in Table 3.

Table 2: Operationalization of the Variables

Variable	Operationalization
Internal Colleagues_Contagion$_{it}$	Number of prescriptions written by the physicians in the same practice as physician *i* until time period *t-1*
External Rivals_Contagion$_{it}$	Number of prescriptions written at time *t-1* by physicians whose practices are in the same neighbourhood of physician *i*'s practice
Knowledge$_{it}$	Number of prescriptions written by physician *i* until and including timeperiod *t-1*
$I_{it}^{Minimum}$	= 1 if the physician *i* at the previous time period (time *t-1) had the least* experience with the product across all physicians in the physician's practice
Tenure$_i$	Number of years physician *i* has been practicing since graduation
University$_i$	=1 if physician *i* is affiliated with an university

Table 3: Descriptive Statistics of the Variables used in the Model

	Variable	Mean	Std. Deviation	Max	Min
1	Internal Colleagues Contagion	0.46	2.05	33.00	0.00
2	External Rivals Contagion	4.81	6.27	33.41	0.00
3	Tenure	18.24	9.69	44.00	3.00
4	University	0.11	0.31	1.00	0.00

We are interested in comparing the coefficients associated with contagion from internal colleagues (γ2) and external rivals (γ3); are they significantly greater than zero, and if so, which one is greater. For interaction effects we are interested in knowing if physicians with less cumulative knowledge are influenced more or less by external rivals, as opposed to internal colleagues. One would expect that, in general, less knowledgeable physicians would be influenced by both sources. Given that learning from internal colleagues is easier than learning from external rivals, one would expect that internal colleagues would matter more than external rivals to less knowledgeable physicians. However, if intra-practice status is an issue, we would expect physicians with greater cumulative knowledge to be less influenced by their internal colleagues versus external rivals. Similarly, if threat plays a role then physicians with minimal experience would tend to seek more from external rivals than internal colleagues. Note that while threat is short-term, status is more long term. It is because of this reason, we operationalize status and threat by cumulative knowledge and last time period relative experience respectively.

The intercept ($\gamma 0i$) captures the intrinsic prescription rate of the physicians. This may vary across physicians, e.g., some physicians may be more popular. In order to get correct estimates it is important to model such unobserved factors. We do so by allowing the intercept, $\gamma 0i$ in the equation 2 to be normally distributed across physicians, i.e. $\gamma\ 0\ i \sim N(\overline{\gamma}0, O^2)$. As discussed earlier, there might be exogenous unobserved variables related to demand shocks (for example, the price of the product, availability of the competitor's product etc.) that can make the physicians prescribe the product more in a particular time period. Failure to account for these correlated unobserved factors can lead to biased estimates of the contagion variables. Therefore, we account for such unobserved time specific variables by incorporating time specific fixed effects.

The final data log-likelihood across all physicians and time periods, LL(θ), is given by:

$$LL(\theta) = \sum_{i=1}^{n} \sum_{t=1}^{T} y_{it} \ln(\lambda_{it}) + \exp(-\lambda_{it}) - \ln(y_{it}!) \qquad (3)$$

where θ represents the vector of all the parameters to be estimated. Since the log-likelihood function given in equation 3 involves integrals over the state space of the parameters, we adopt a Monte- Carlo simulation approach and estimate the model via simulated maximum likelihood (see McFadden and Train 2000 for details).

Results

In this section, we first compare the fit of our proposed model against the fit of alternative models. To benchmark our proposed model of contagion we estimated two different alternative models. In the first alternative model (Model 1), we do not account for either of the contagion variables. In the second alternative model (Model 2), we account for the main effects of the two contagion variables (internal colleagues and external rivals), but not for the interaction effects. Model 3 is our proposed model in which we account for the main effects and the interaction effects of the two contagion variables.

We find that in terms of model fit, Model 2 that accounts for the two contagion variables fits the data better than Model 1 that does not account for the contagion variable. Analysing the Bayesian Information Criterion (BIC)[6] of Model 2 and Model 1 (8975.94 for Model 2 vs. 9070.92 for Model 1) suggests that the model that accounts for contagion from internal colleagues and external rivals fits the

[6] We note that a lower BIC indicates a better model fit.

data better. Comparing the BIC of Model 3 and Model 2 (8945.80 for Model 3 vs. 8975.94 for Model 2) demonstrates that our proposed model, with the interactions effects of status and threat with contagion variables, fits better than the model without interaction effects. The improvement in model fit that we find in terms of BIC is also in conformance with the likelihood ratio test. The test favours Model 2 over Model 1 and our proposed model (Model 3) over Model 2. Table 4 presents the in-sample fit statistics of the three models.

Table 4: Comparison of Model Fit

Model	**LL**	**BIC**
Model 1: Model without any contagion effects	-9000.05	9070.92
Model 2: Model 1 that accounts for main effects of contagion due to internal colleagues and internal rivals	-8896.73	8975.94
Model 3: Model 2 that accounts for interaction effects with contagion due to internal colleagues and internal rivals	-8849.91	8945.80

Notes: LL: Log-Likelihood; BIC: Bayesian Information Criterion BIC=-LL+0.5 x k x ln(n) where k is the number of parameters in the model and n is the number of observations. A lower BIC indicates a better model fit

Since our proposed model has the best fit, we discuss the results of proposed model. The results of the proposed model are presented in Table 5.

Table 5: Results of the Poisson Model of Physicians' Prescription Behaviour: Contagion Due to Internal Colleagues Versus External Rivals

Variable	Model 3: Parameter Estimate
Knowledge	$.74^{***}$
Internal Colleagues_Contagion	$.20^{**}$
External Rivals_Contagion	$.17^{**}$
Knowledge* Internal Colleagues_Contagion	-0.06**
Knowledge * External Rivals_Contagion	-0.02
$I_{it}^{Minimum}$* Internal Colleagues_Contagion	-0.08*
$I_{it}^{Minimum}$* External Rivals_Contagion	-0.04*
University	.21
Tenure	$.12^{+}$
Intercept ($\bar{\gamma}_0$)	$.31^{***}$
Unobserved heterogeneity (σ^2)	0.98^{*}
Log-likelihood (LL)	-8849.91
BIC	8945.80

Notes: a) The LL improvement of the proposed model (Model 3) over the null (without the main and the interaction effects of the two contagion variables) is significant at the 0.01 level (the calculated χ^2 is 300.28, whereas the critical $\chi^2(6, 0.01) = 16.82$).

*** $p \leq .001$, ** $p \leq .01$, * $p \leq .05$, $^{+}$ $p \leq .10$

The results of the model find support for the significant effect of contagion on physicians' prescription behaviour. The results suggest that the two sources of contagion, i.e., internal colleagues ($\gamma2$=.20, $p \leq .01$) and external rivals ($\gamma3$=.17, $p \leq .01$) are both positive and significant but contagion from internal colleagues has a marginally greater effect than from external rivals. The results of the model also suggest that physicians learn from their own experience with the product ($\gamma1$=.74, $p \leq .001$).

Turning our attention to the interaction effects, we find that physicians with greater cumulative prior knowledge are less influenced by internal colleagues ($\gamma4$=-.06, $p \leq .01$). There is no significant interaction effect between physicians' cumulative prior knowledge and external rivals ($\gamma5$=-.02, non-significant). We find evidence of status in knowledge sharing in that those physicians who have less experience would actually seek information from their external rivals as opposed to physicians within their own practice. We also find that physicians who have the least product experience in their practice are less likely to be influenced by either internal rivals ($\gamma6$=-.08, $p \leq .01$) or external colleagues ($\gamma7$=-.04, $p \leq .01$). To sum, physicians with the least relative experience are less likely to learn from internal colleagues as compared to external rivals. Taken together, the above results indicate that while physicians rely on both internal colleagues and external rivals for knowledge, there are behavioural issues that can impede their willingness to learn from internal colleagues.

With respect to physician specific control variables, our results suggest that the prescription rate of physicians with greater tenure are marginally higher, and that there is no significant difference in the prescription rate of physicians who are affiliated to universities when compared to physicians who are not affiliated to universities. Finally, with respect to the time fixed effects, we find that 9 out of 12 were significant with the absolute value of t-statistic greater than 1.65 (p-value of ≤ 0.10).

Discussion and Conclusions

The purpose of our study is to examine how workers learn about a new technology from two personal sources and the effect of employee characteristics on such learning. To accomplish our objectives, we use a unique panel data of specialist physicians' prescription of a new medical technology.

We find that physicians are influenced by both internal colleagues and external rivals with internal colleagues having a marginally greater influence than external rivals. Evidence for status and threat are seen in that physicians who are most knowledgeable and physicians who are least knowledgeable tend to seek more from external sources rather than internal. We believe that our study is one of the first to use actual choice data to shed light on such behavioural issues in workers' learning via social contagion.

We believe that our findings have implications for managers in that it will help firms decide how to facilitate knowledge exchange in light of the different roles played by peers. One possible option may be to use information and communication technologies that are available to make learning and knowledge sharing between employees easier. Yet, based on the results of our study, we believe that if information technologies are impersonal and if they do not promote face-to-face virtual interaction, they may actually amplify the behavioural issues and thus may prove counterproductive. Our results emphasize the need for managers to build a team spirit and friendships between team members in order to lower the perception of threat for with least knowledgeable employees. Managers may schedule informal sessions that can help break the shackles of threat and personal status for better flow of information flow between workers. One could go further and suggest getting the least and most knowledgeable inside the organisation to come together informally. On the external front possible structured sessions with professional colleagues is to be encouraged.

Although our study is one of the first attempts to analyse the dynamic and behavioural issues in knowledge transfer between workers using behavioural data, it is not without its limitations. Our study is the context of physicians' prescription behaviour. Future studies can look into other contexts and test for the generalizability of our findings. It would also be interesting to assess if information technologies amplify or mitigate the behavioural issues in knowledge transfer. In conclusion, we hope that our study helps to understand the issues involved in transfer of knowledge across workers in an organisation and that it will spawn further research in this important area.

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