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# The Dynamic Impacts of Online Healthcare Community on Physician Altruism: A Hidden Markov Model

*Short Paper*

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*"The medical profession is too important to society to allow its future to be determined by market forces."*
-- Arnold S. Relman, M.D., Harvard Medical School

## Introduction

Physician altruism, which lies at the core of medical professionalism, underpins the principle of primacy of patient welfare and the fundamental ethical value system built upon the belief that the medical profession exists to serve patients' and the public interests (ABMS 2012). However, mainstream voices in the medical field have long expressed great concerns that this value system is under siege in the modern environment in facing of the explosion of technologies and changing market forces (e.g., Coulehan 2005; Relman 2007). Hence, understanding the influence of the modern environment on physician altruism is an urgent matter to both researchers and policy makers related to the medical field.

In spite of the considerable importance of this topic, surprisingly little is known empirically. First, the bulk of past research efforts have been largely limited to qualitative assessments and opinions (e.g., Brainard and Brislen 2007; Kinghorn et al. 2007). They seem to unanimously suggest that modern market and technological advancements influence negatively on physician altruism. Sufficient explorations of the underlying theoretical mechanism are, however, amiss here. Second, and perhaps more importantly, such uniform "negativity" presented in the past literature may potentially hinder progress in practice as they carry limited policy or practical implications regarding what promotes or undermines physician altruism. To rectify the situation, we utilize the unique opportunity offered by the emergence of online healthcare communities (OHCs) to provide an initial quantitative assessment of the real impacts of one of the current healthcare digitization trends on physician altruism to inform both theory and practice.

The emergence of online healthcare communities[1] can be viewed as part of the Internet-based digitization efforts of healthcare in the past two decades (Agarwal et al. 2010). They are not technological advancements that aim to improve medical techniques but that facilitate better healthcare service delivery. The demand for such digital service has soared in recent years. For example, Pew has discovered that one in three American adults have gone online to figure out a medical condition (Pew 2013), while Google has uncovered that more than 77% of the U.S. patients used search engines prior to booking appointments (Google 2012).

[1] There are online healthcare communities that are comprised of only patients (e.g., PatientLikeMe). However, in this study, we will be focusing only on online healthcare communities that are comprised of both patients and physicians.

On the supply side, private initiatives across the globe have also already begun to build Internet start-ups[2] to accommodate such demand. They represent contemporary commercial as well as technological efforts to revolutionize the way patients and physicians connect to each other. As they are gaining tractions nowadays, studying their impacts on physician altruism has the potential to yield significant implications.

As with past altruism studies, we view physician altruism as an inherent but dynamic construct that underlies an individual's psychological tendency to benefit others without self-gain or even at the cost of oneself (Krebs 1970). However, in contrast to most studies of human altruism that are conducted in the laboratory experiment settings (e.g., Berman et al. 2018; Fehr and Fischbacher 2003) where static observations of altruism are collected, we are interested in empirically analyze the *dynamics* of physician altruism in the context of online healthcare communities. More specifically, we focus on various IT artifacts of the online healthcare communities that aim to give participating physician both the social and economic returns. While the design of these IT artifacts can be instrumental in motivating physicians to participate and stay in the online community (Guo et al. 2017), they might also exhibit collateral influence on physician altruism. As such, we propose the following research question: *what is the dynamic influence of different IT artifacts of an online healthcare community on physician altruism?*

To empirically answer our research question, we propose a *Hidden Markov Model* (HMM) that characterizes the dynamics of physician behaviors on the OHCs with different hidden psychological altruism states, as well as the dynamic transition between the states. With a unique panel data set collected from one of the largest online healthcare communities in China, we will use Bayesian estimation to provide identification and inference on the dynamic influence of various IT artifacts.

With preliminary evidence, we expect to find both the positive and negative impacts of different IT artifacts on physician altruism. By exploring such contrasting influences, our study has the potentials to advance our theoretical knowledge of the influence of market activities on physician altruism while carrying significant implications for both the policymakers and the practitioners. We aim to make a few key theoretical contributions. First, to the best of our knowledge, we will be among the firsts to study the dynamics of physician altruism in a large-scale real-world setting, which are absent in a traditional laboratory setting. Second, answering the calls for studying the impact of Health IT (Agarwal et al. 2010), this study provides a critical initial assessment on the societal impacts of the digitized healthcare service on physician altruism. And finally, we also wish to contribute to the economic theories of human altruism by explicating the underlying mechanisms through which physician altruism can be promoted or undermined.

The rest of the paper is organized as follows. In the next section, we review the related literature on physician altruism and human altruism in general. Then, we layout the research context and the proposed structural *Hidden Markov Model*. After describing the data, we will present the results of the preliminary analyses. Finally, we discuss the potential contributions of this study and the step forwards.

## Literature Review

### *Human Altruism*

At the conceptual level, human altruism is considered as both social behavior and an inherent personality attribute (Krebs 1970). As a personality attribute, researchers define it as a psychological state or tendency to benefit others without self-gain or even at the cost of oneself (Krebs 1970). Researchers have also suggested that there is considerable heterogeneity in altruism across humans and it can change dynamically through personal development (e.g., Batson et al. 1987; Weng et al. 2013).

As a social behavior, behavioral scientists define it in a more "forgiving" manner that does not require proving the intention behind the behavior. As Krebs (1975) summarized, as helping behavior, it is "the extent of self-sacrifice, the expectation of gain, and the orientation to the needs of another that define acts as altruistic (p.1134)." More specifically, it is the absence of the expectation of external gains that distinguishes altruistic behavior from other helping behaviors like prosocial behavior (Underwood and Moore 1982). Along this line, subsequent behavioral studies further develop a simple operational definition

[2] For example, *YourDoctors.Online* in the U.S.; *Haodf.com* in China; *MonkMed* in India; *UKMeds.co* in the UK.

of altruism. For example, in their paper, Fehr and Fischbacher (2003) define altruism as "costly acts that confer economic benefits on other individuals (p.785)."

No matter the behavioral definition of altruism, researchers have emphasized that the seemingly "altruistic" responses are affected by the corresponding psychological state (e.g., Andreoni et al. 2017; Krebs 1970). More importantly, the psychological state is considered as a temporal state that is subjected to the influence of various external factors, such as, recipient characteristics (Krebs 1975), emotional closeness (Korchmaros and Kenny 2001), or even the ambient temperature of the environment (Lynott et al. 2017).

### *Physician Altruism*

While the medical professionals often define physician altruism as a principle or ethical value system (ABMS 2012), health economics researchers generally define physician altruism as the tradeoff a physician makes between improving patients' welfare and monetary self-interest (Godager and Wiesen 2013). In other words, physicians with a higher degree of altruism tend to attach higher weights to patients' welfare than material self-interest. More importantly, they assume that every physician is, although to a varying degree, altruistic in nature (Arrow 1963). Otherwise, the healthcare market would breakdown under severe information asymmetry. Assumptions on physician altruism are, hence, essential in the theoretical health economics literature, for the design of optimal payment model scheme (Choné and Ma 2011), the delegation of treatment decision (Liu and Ma 2013), referral decision (Allard et al. 2011), and etc. In spite of its considerable importance, scant empirical attention has been dedicated to understanding what influences physician altruism. Of the handful of studies that empirically explored the heterogeneity in physician altruism (e.g., Godager and Wiesen 2013), they studied physician altruism in laboratory experiment settings that do not allow for dynamic observations. The same is observed in the wealth of the theoretical health economics literature where the dynamic change to physician altruism is rarely considered.

To fill the gap in the literature, we define physician altruism as a *psychological state that characterizes a physician's internal balance between her patients' welfare and her material self-benefits*. However, we allow this state to change dynamically as a result of receiving social and economic gains from participating in an OHC overtime. Finally, the outcomes of physicians' dynamically-changing altruism states are captured using the observable altruism-related physician behaviors on the OHC.

## Research Context

We situate this study at Haodf.com, a leading OHC in China. It provides an openly-assessible online catalog of nationwide hospitals and certified physicians. Interested physicians could join the community and open a personal website with online text consultation functions. Online patients, on the other hand, could initiate one-to-one text consultation on the website of any physician of their choice free-of-charge. The text consultation proceeds in an unsynchronized post-and-reply closed forum fashion (closed in the sense that only the focal patient and focal physician are allowed to contribute to the thread). A patient posts her medical question on a physician's website. The physician replies to the question when she is available. Although the text consultation is free-of-charge to the online patients, the patients could also opt to purchase premium service (e.g., paid telephone consultation) from the online physicians.

As an online business, Haodf.com faces the challenge of retaining online physicians to attract the traffic of online patients. As suggested by Guo et al. (2017), some of the key motivations for physicians to join such online communities are the prospect of earning some social and economic returns. To cope with this, Haodf.com employs various mechanisms. To provide physicians with social/reputational returns, it provides the physician "rating" feature. In each online consultation, the patient could provide simple star ratings for the physician. More unique to the healthcare aspect is the "thanks letter" feature, which is similar to online physician reviews. However, while physician reviews often contain both the positive and negative feedbacks, the thanks letter only conveys elaborated verbal appreciation from the online patients.

There are also features that give physician direct economic benefits. In the online consultation, the patient could voluntarily send a virtual gift to the physician as a token of appreciation. The virtual gift needs to be purchased with real money and the physician would receive a portion of the money for the gifts she received. In addition to the virtual gift, the patients could also choose to purchase premium service (e.g., paid telephone consultation) from the physician. The premium service is relatively more costly (for example, a

20-minute telephone consultation could cost a patient 180 RMB or equivalently around 26 USD). The physician would then receive a direct transactional monetary return from the purchase.

# Model Development

We first provide a simple mathematical expression of the physician altruism defined in this paper. We assume that a physician $i$ at a given time $t$ intrinsically attach a weight $a_{it}$ to the unit welfare of a patient. Meanwhile, she also attaches a weight $b_{it}$ to a unit of self-benefits. Then, physician altruism is captured by

$$\lambda_{it} = a_{it} / b_{it} \tag{1}$$

which is her internal balance between patient welfare and self-benefits. With this expression, a higher value for $\lambda_{it}$ suggests that the physician places a relatively higher weight to patient welfare over her self-benefits and vice versa. We note that this simple expression is also in line with the psychological definition of human altruism as it can also be interpreted as the degree of tendency to benefit the patients at the cost of oneself.

We now describe the HMM model. There are three main components in the model: i) we model physicians with different hidden altruism states, with 1 being the lowest altruism degree and $K$ being the highest. At any given time $t$, a physician could only be in one state; ii) from time *t-1* to $t$, a physician could switch to any state with certain probability, which is affected by her interactions (e.g., receiving social and economic returns) with the OHC in time *t-1*; and iii) conditional on the altruism state in time $t$, we capture different aspects of the physician's online reply to the patients as the state-dependent outcomes.

## *Hidden Altruism State Transition*

From time t-1 to t, a physician may stay in one state, or switch to a higher or lower state. We characterize the probability of all possible transitions between states with $Q_{it}$ which is defined as:

$$Q_{it} = \begin{pmatrix} q_{i11t} & \cdots & q_{i1Kt} \\ \vdots & \ddots & \vdots \\ q_{iK1t} & \cdots & q_{iKKt} \end{pmatrix}$$

where $q_{ikjt} = P(s_{it} = j \mid s_{i,t-1} = k)$ is the transition probability from state $k$ to state $j$, and $\sum_j q_{ikjt} = 1$ for all $k, j \in \{1, \ldots, K\}$. We assume that $q_{ikjt}$ is influenced by a physician's interactions (i.e., receiving gifts, thanks letters, ratings, and purchases) with the OHC in the previous time period. Upon receiving different social and economic returns on OHC, a physician may reevaluate her internal weights assigned to patient welfare or self-benefits, resulting in fluctuations in $\lambda_{it}$. If $\lambda_{it}$ increases, she would be more likely to switch to or maintain a high altruism state. Otherwise, she may descend to a lower altruism state. Following Yan and Tan (2014), we model $Q_{it}$ using an ordered logit model specified as follows:

$$\begin{gathered}
q_{isKt} = 1 - \frac{\exp(\overline{\omega}_{s\to K} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}{1 + \exp(\overline{\omega}_{s\to K} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}; \\
q_{is(K-1)t} = \frac{\exp(\overline{\omega}_{s\to K} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}{1 + \exp(\overline{\omega}_{s\to K} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)} - \frac{\exp(\overline{\omega}_{s\to K-1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}{1 + \exp(\overline{\omega}_{s\to K-1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}; \\
\ldots \\
q_{isst} = \frac{\exp(\overline{\omega}_{s\to s+1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}{1 + \exp(\overline{\omega}_{s\to s+1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)} - \frac{\exp(\underline{\omega}_{s\to s-1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}{1 + \exp(\underline{\omega}_{s\to s-1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}; \\
\ldots \\
q_{is2t} = \frac{\exp(\underline{\omega}_{s\to 2} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}{1 + \exp(\underline{\omega}_{s\to 2} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)} - \frac{\exp(\underline{\omega}_{s\to 1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}{1 + \exp(\underline{\omega}_{s\to 1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}; \\
q_{is1t} = \frac{\exp(\underline{\omega}_{s\to 1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}{1 + \exp(\underline{\omega}_{s\to 1} - \boldsymbol{\beta}_s \boldsymbol{X}_{i,t-1} - \boldsymbol{\xi}_i)}
\end{gathered} \tag{2}$$

Here, $s$ is the current state, where $\underline{\omega}_{s\to k}$ is the threshold for transition from current state $s$ to a lower state $k$ ($k<s$) and $\overline{\omega}_{s\to k}$ is the threshold for transition from current state $s$ to a higher state $k$ ($k>s$). For any given $s \in \{1, \dots, K\}$, we have $\overline{\omega}_{s\to K} \geq \overline{\omega}_{s\to K-1} \geq \cdots \geq \overline{\omega}_{s\to s+1} \geq \underline{\omega}_{s\to s-1} \geq \cdots \geq \underline{\omega}_{s\to 2} \geq \underline{\omega}_{s\to 1}$. And vector $\boldsymbol{\omega}$ denotes all possible threshold values. The vector $\boldsymbol{X_{i,t-1}}$ contains lagged variables related to physician's previous experience on the OHC that have an impact in terms of physician's switching between states. The vector $\boldsymbol{\beta_s}$ is a set of state-dependent parameters. And finally, $\xi_i$ captures the individual unobserved heterogeneity. At last, we assume that when a physician first joins the online community, the initial probability of being in hidden state $k$ is determined by the vector $\boldsymbol{\pi} = \{\pi_1, \pi_2, \dots, \pi_K\}$ and $\sum_{j=1}^{K} \pi_j = 1$.

### *State-Dependent Outcomes*

As per our definition of physician altruism and its mathematical expression with $\lambda_{it}$, conditional on the altruism state, the physician could exhibit different reply patterns to the free online consultation from online patients. In this paper, we identify physician solicitation of patients as one of the unique patterns that is strongly influenced by the fluctuating altruism state. Solicitation of patients involves direct contact with patients regarding the possibility of rendering service to them (Physicians Practice 2011). In the online healthcare community, physician solicitation could manifest as the physician asking the online patients to visit her offline or purchase premium service online in her text replies. As such, physician solicitation is relevant in two important aspects. First, a higher rate of solicitation implies that the physician has relatively higher weights ($b_{it}$) assigned to her self-benefits, which correspondents with a lower physician altruism level ($\lambda_{it}$). Second, the presence of solicitation also implies that the physician is expecting additional direct monetary self-benefits from the online patients, which immediately render the behavior as non-altruistic according to the behavioral definition of altruism. In short, we contend that the solicitation behavior is not only unique in the OHC context but is also determined by the hidden physician altruism state.

We model the solicitation behavior at the physician-weekly level. While solicitation in a given consultation is a binary variable, at the weekly level, it captures the rate of solicitation among all online consultations in the week. For the ease of interpretation, we use $Y_{it}$ to denote the rate of non-solicitation in week $t$ so that higher value of $Y_{it}$ is corresponded with a higher altruism state. As $Y_{it}$ is a continuous rate that is restricted to the interval [0,1], we model the conditional probability ($Y_{it}|s_{it}$) using the beta regression developed by Ferrari and Cribari-Neto (2004). For any given $Y_{it}$ conditional on $s_{it}$, the probability density function is:

$$f_s(\boldsymbol{Y_{it}}|\boldsymbol{W_{it}}, \boldsymbol{\gamma_s}, \boldsymbol{\phi_s}) = \frac{1}{\mathrm{B}\big(g(\boldsymbol{W_{it}}, \boldsymbol{\gamma_s})\boldsymbol{\phi_s}, \big(1-g(\boldsymbol{W_{it}}, \boldsymbol{\gamma_s})\big)\boldsymbol{\phi_s}\big)} \cdot \boldsymbol{Y_{it}}^{g(\boldsymbol{W_{it}}, \boldsymbol{\gamma_s})\boldsymbol{\phi_s}-1} \cdot (1-\boldsymbol{Y_{it}})^{(1-g(\boldsymbol{W_{it}}, \boldsymbol{\gamma_s}))\boldsymbol{\phi_s}-1} \tag{3}$$

$$g(\boldsymbol{W_{it}}, \boldsymbol{\gamma_s}) = \frac{\exp(\boldsymbol{\gamma_s}\boldsymbol{W_{it}} + \boldsymbol{\eta_i})}{1+\exp(\boldsymbol{\gamma_s}\boldsymbol{W_{it}} + \boldsymbol{\eta_i})} \tag{4}$$

where $\mathrm{B}(\cdot)$ is the beta function and $\mathrm{g}(\cdot)$ is the logistic function. $\phi_s$ is the state-dependent distribution precision parameter. The vector $\boldsymbol{W_{it}}$ comprises variables that have a direct impact on $Y_{it}$, while $\boldsymbol{\gamma_s}$ is the corresponding vector that contains the state-dependent parameters. Finally, $\eta_i$ is the physician-specific random effects that accounts for unobserved individual physician heterogeneity. In essence, $g(\boldsymbol{W_{it}}, \boldsymbol{\gamma_s})$ captures the expected value of $Y_{it}$ and restricts the value to the interval (0, 1).

Integrating Equation (2), (3), and (4) together, we can write the likelihood function of observing a sequence of outcomes $\{Y_{i1}, Y_{i2}, \dots, Y_{iT}\}$. We estimate the model parameters using a hierarchical Bayesian framework (Ascarza et al. 2018) that updates the posterior distribution by incorporating the observed information from the data. To ensure the identification of the states or preventing the "label switching" problem (Jasra et al. 2005), we restrict the $\gamma_s$ parameters for the constant term in $\boldsymbol{W_{it}}$ to be increasing with the altruism states.

## Preliminary Analysis and Results

### *Sample and Variables*

To test our model, we construct a physician-week panel of 483 physicians in 52 weeks of the year 2012. We choose the year 2012 for two important reasons: 1) six years after it was launched, the usage of this OHC should be less of a new shock to both the physicians and patients, 2) according to its website, there was no major feature update to this OHC in 2012 such that no common external shock would contaminate our results. We sampled only the physicians who joined the OHC prior to 2012 and had a total number of consultations between 200 and 2,000 in 2012. Finally, we only sampled physicians from one major city (i.e., Shanghai) in China to reduce computational complexity. In total, there are more than 300,000 online text consultations belong to the 483 physicians in 2012.

To generate the dependent variable, we conducted content analyses on the physician reply texts. We employed two independent research assistants to manually code more than 27,000 randomly selected actual text replies from the OHC. Specifically, we code whether the physician is soliciting the online patient to a) visit her offline or b) purchase telephone consultation with her. With 70% of the labeled text sample as the training data, we train a variant of CNN text binary classification model (Kim 2014). We evaluate the performance of the model with the remaining 30% hold-out sample. With testing accuracy and $F_1$ score exceeding 95% for both tasks, we deploy the classifiers to the full text sample. A text reply is considered as a non-solicitation reply if it contains no offline solicitation and paid telephone solicitation information.

Table 1 presents the definitions of our variables and descriptive statistics. We categorize the explanatory variables into two groups: interactions on the OHC ($\boldsymbol{X_{i,t-1}}$) and patients and physicians characteristics ($\boldsymbol{W_{it}}$). The interactions on the OHC have a direct impact on a physician's hidden state transition probability. As have discussed in the research context, $Letters_{i,t-1}$ and $Ratings_{i,t-1}$ capture the social/reputational returns to the physician in time *t-1*. Receiving thanks letters and ratings from the online patients could directly improve the physician's reputation, image, and social status both on the online community. However, the elaborated verbal thanks letters are considerably more powerful and informative than star ratings. On the other hand, $Gifts_{i,t-1}$ and $Purchases_{i,t-1}$ capture the direct economic returns to the physician in time *t-1*. While voluntary gifts represent a monetary token of appreciation, remunerations from service purchases equate to earnings from fulfilling a transaction. In short, although receiving those interactions from the OHC all represent the realization of social or economic returns to the physician, due to their difference, it would be interesting to explore how they might influence a physician's hidden altruism state differently.

**Table 1. Variables and Descriptive Statistics**

| Variables | Description | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|
| ***Dependent Variable ($Y_{it}$)*** | | | | | |
| $Non\_Solicitation_{it}$ | Ratio of non-solicitation consultations | 0.759 | 0.263 | 0 | 1 |
| ***Interactions on the OHC ($X_{i,t-1}$)*** | | | | | |
| $Gifts_{i,t-1}$ | Number of gifts received by the physician | 0.438 | 1.213 | 0 | 23 |
| $Letters_{i,t-1}$ | Number of thanks letters received by the physician | 0.045 | 0.273 | 0 | 7 |
| $Ratings_{i,t-1}$ | Number of online ratings received by the physician | 0.093 | 0.486 | 0 | 13 |
| $Purchases_{i,t-1}$ | Number of service purchases received by the physician | 0.141 | 0.597 | 0 | 13 |
| ***Patients and Physicians Characteristics ($W_{it}$)*** | | | | | |
| $\#\_Patients_{it}$ | Number of unique online patient text consultations | 12.318 | 10.332 | 1 | 109 |
| $Weekend\_Replies_{it}$ | Ratio of replies in the weekend | 0.256 | 0.279 | 0 | 1 |
| $Local\_Ratio_{it}$ | Ratio of online local patients (from Shanghai) | 0.305 | 0.247 | 0 | 1 |
| $Lens\_Posts_{it}$ | (log) Mean lengths of online patients' text posts | 5.134 | 0.332 | 0.692 | 7.629 |
| $Total\_Patients_{i,t-1}$ | (log) Total number of past online patients of the physician | 5.147 | 1.358 | 3.688 | 9.260 |
| *Senior_Physician* | Whether the physician is a senior physician or not | 0.481 | 0.499 | 0 | 1 |
| *Surgical* | Whether the physician is in the surgical department or not | 0.510 | 0.500 | 0 | 1 |
| Number of observations: 22,793. | | | | | |

Note: in the estimation, $\#\_Patients_{it}$ is rescaled (divided by 10).

The variables in vector $\boldsymbol{W}$ captures factors that could directly influence physician solicitation behaviors. We suggest that contextual factors such as busyness, effort level, and potential of successful solicitations would temporally influence the likelihood for the physician to solicit (or not solicit) online patients. We use the number of online patients ($\#\_Patients_{it}$) and patients' post length in the text consultation ($Lens\_Posts_{it}$) to capture the busyness and potential level of effort the physician needs to put into the online consultation in a week. The physician could also subjectively view non-working day replies ($Weekend\_Replies_{it}$) as more effortful. The ratio of local online patients ($Local\_Ratio_{it}$) captures the potential of successful solicitations as local patients are more likely to visit her offline. The last three variables contain the physician characteristics, such as cumulative popularities on the OHC, senority, and department affiliation.

### *Preliminary Estimation Results*

We write our own Bayesian algorithm to estimatie the model. Currently, we are in the phase of fine-tuning our algorithm to get a stable and consistent result. Nonetheless, to provide some preliminary insights into what our final results might look like, Table 2 presents the preliminary Bayesian estimation results of a three-state HMM without estimating individual heterogeneity.

For ease of discussion, we refer to the three altruism states as low (L), normal (N), and high (H) altruism state. Indeed, the medical profession is a noble profession as all physician take the Hippocratic Oath. The initial probability of being in the L, N, and H state are 6.3%, 82.3%, and 11.4%. And corresponding mean posterior non-solicitation ratio are 45.9%, 72.3%, and 92.5%. In essence, a new physician tends to be in the normal altruism state rather than the other two states.

For the preliminary insights, we will focus on interpreting the estimated coefficients for the state transition probabilities. As per our model specification, we provide a simple way of interpreting the coefficients for $X_{i,t-1}$ in each state. Taking the coefficients for $Gifts_{i,t-1}$ for example, a positive (negative) coefficient implies that receiving more gifts, holding other covariates constant, on the OHC would increase the probability of the physician moving to a higher (lower) altruism state. As such, our preliminary results suggest that receiving additional gifts and ratings will increase the likelihood of a physician switching to a lower altruism state. On the contrary, receiving additional thanks letter will increase the likelihood of a physician switching to a higher altruism state. The results for receiving an additional purchase, however, are mixed. If the physician is already in the high altruism state, the likelihood of the physician stays in the high altruism state increases. Otherwise, she is more likely to switch to a low altruism state.

**Table 2. Preliminary Bayesian Estimation Results**

| Variables | State L (Low Altruism State) | State N (Normal Altruism State) | State H (High Altruism State) |
|---|---|---|---|
| $\boldsymbol{X_{i,t-1}}$ | $\beta$ - Posterior Mean (Standard Deviation) | | |
| $Gifts_{i,t-1}$ | -1.092*** (0.020) | -0.871*** (0.006) | -0.420*** (0.035) |
| $Letters_{i,t-1}$ | 1.072*** (0.010) | 0.117*** (0.010) | 2.678*** (0.041) |
| $Ratings_{i,t-1}$ | -0.825*** (0.021) | -1.028*** (0.013) | -1.568*** (0.027) |
| $Purchases_{i,t-1}$ | -0.507*** (0.019) | -1.923*** (0.017) | 2.149*** (0.014) |
| $\boldsymbol{\omega}$ | Posterior Mean (Standard Deviation) | | |
| *State L* | - | 0.677*** (0.119) | 3.035*** (0.016) |
| *State N* | -2.413*** (0.273) | - | 0.684*** (0.023) |
| *State H* | -3.808*** (0.066) | -1.075*** (0.003) | - |
| $\boldsymbol{W_{it}}$ | $\gamma$ - Posterior Mean (Standard Deviation) | | |
| *Constant* | -1.340*** (0.035) | -0.045*** (0.009) | 2.842*** (0.066) |
| $\#\_Patient_{it}$ | 0.065*** (0.006) | 0.162*** (0.015) | -0.379*** (0.021) |
| $Weekend\_Replies_{it}$ | 0.899*** (0.012) | 0.079*** (0.011) | 0.190*** (0.011) |
| $Local\_Ratio_{it}$ | -0.722*** (0.019) | -0.704*** (0.006) | -0.305*** (0.014) |
| $Lens\_Post_{it}$ | 0.123*** (0.008) | 0.332*** (0.008) | -0.054 (0.042) |
| $Total\_Patients_{i,t-1}$ | -0.049*** (0.010) | -0.143*** (0.002) | -0.037*** (0.004) |
| *Senior_Physician* | 0.868*** (0.019) | 0.479*** (0.016) | 1.061*** (0.016) |
| *Surgical* | 0.558*** (0.010) | -0.387*** (0.010) | 0.264*** (0.020) |
| $\boldsymbol{\phi}$ | 0.706*** (0.017) | 6.283*** (0.075) | 7.893*** (0.032) |
| *Initial Probability* | 0.063*** (0.008) | 0.823*** (0.012) | 0.114*** (0.011) |

Note: * p<0.1; ** p<0.5; *** p<0.01.

## Potential Contributions and Next Steps

Despite being a short paper, our study aims to make the following critical contributions to the literature. First, to the best of our knowledge, this study is among the firsts in the emerging literature to empirically investigate the physician altruism in a large-scale real-world setting. More specifically, using a Hidden Markov Model, we paint a dynamic picture of physician altruism that is seldom captured in both the medical and health economics literature (e.g., Choné and Ma 2011; Godager and Wiesen 2013; Relman 2007). Second, our study adds to a more nuanced understanding of the impact of healthcare information technology (e.g., Agarwal et al. 2010; Majchrzak et al. 2016). The observed divergent impacts of different

IT artifacts implemented by the online healthcare communities on physician altruism provide the supporting evidence for the important yet complex alternative conceptualization of health IT artifact at the societal level. Third, we will also contribute to the stream of economics literature on altruism (e.g., Andreoni et al. 2017; Fehr and Fischbacher 2003) by explicating the nature of physician altruism on an online healthcare community. More specifically, we document how different motivating mechanisms (i.e., gaining social and economic returns) of an online community can promote or undermine physician altruism.

For the next steps, we will continue fine-tuning our Bayesian estimation algorithm and conduct model selection procedures. We will incorporate heterogeneity into the model estimation to get more generalizable and comprehensive results. In addition to the main analysis, we also propose several ways to test the robustness of our results: 1) we will explore other ways to operationalize the altruism state-dependent outcomes using the physician replies; 2) we will test the model on different samples (e.g., physicians from a different city); and 3) we will add additional control variables into the model to test the variations of the results. At last, we will conduct several different design simulations to gain further theoretical as well as practical insights.

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