Doctors' Orders or Patients' Preferences? Examining the Role of Physicians in Patients' Privacy Decisions on Health Information Exchange Platforms

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Abstract

Health information exchange (HIE) platforms could increase the efficiency of health care services by enabling providers to instantly access the medical records of their patients. However, these benefits cannot be realized unless patients disclose their information on HIE platforms. We examine actual privacy decisions made by patients on an HIE platform, study the influence of physicians' recommendations on patients' decisions, and explore the process through which this effect takes place. By analyzing a unique data set consisting of the privacy decisions of 12,444 patients, we show that contrary to common belief, patients do not simply follow physician recommendations, but rather carefully consider the risks and benefits of providing consent. We show that competition among medical providers does not hinder patient participation in HIEs, but that providers' decisions to ask for consent are primarily driven by the potential benefits of HIE for themselves and their patients.

Keywords: Health Information Exchange, Patient Privacy, Information Disclosure.

1 Introduction

A health information exchange (HIE) is a multisided platform that connects different stakeholders in the health care market and enables them to electronically share the medical information of their patients with each other (Kuperman, 2011; Miller & Tucker, 2014). Although HIE platforms have the potential to radically improve the quality and reduce the costs of medical services (Janakiraman, Park, Demirezen, & Kumar, 2017; Miller & Tucker, 2011a; Yaraghi, 2015), increasing the number of patient consents is of critical importance to the success of these platforms (Adler-Milstein, Bates, & Jha, 2011; Petrova, M. Barclay, S. S. Barclay & S. I. G. Barclay, 2017). The numerous challenges in managing and protecting patient privacy

(Miller & Tucker, 2011b; Yaraghi & Gopal, 2018) impede the growth and expansion of HIE systems (Yasnoff, 2016), therefore shedding light on the factors that affect patients' privacy choices is of significant importance to policy makers and practitioners.

From a theoretical perspective, the process of information disclosure on HIE platforms is unique and warrants careful examination. This is due to the fact that the decision to disclose information is not made by patients independently and is rather affected by the preferences of both patients and their physicians. So far, the literature has focused on individuals as the sole decision makers and has not yet examined the settings in which the privacy decision of an individual is affected by the preferences of others. As we discuss later in the paper, privacy decision-making in the HIE

context is a two-stage process in which patients can make a decision about sharing their medical records only after they are asked by a medical provider. In other words, patients cannot make a decision unless medical providers give them a chance to do so; therefore, ignoring the role of medical providers and modeling the observed privacy choice as a function of the utility of the patient alone will lead to incorrect inferences.

From the empirical perspective, since this study relies on actual privacy decisions rather than stated preferences, its conclusions do not suffer from the privacy paradox (Norberg, D. R. Horne, & D. A. Horne, 2007), which implies that contrary to planned behavior theory (Ajzen, 1991), individuals continue to willingly disclose their private information despite growing concerns over their privacy (Madden, Fox, Smith, & Vitak, 2007).

The purpose of our research is to bridge the above-mentioned theoretical and empirical gaps by modeling privacy decision-making in the context of an HIE platform as a process that involves medical providers and patients as two distinct but related agents. Our research identifies the factors that determine the choices of medical providers and patients to, respectively, ask for, and provide consent, and illuminates the extent to which physicians influence their patients' decisions. In this research, we rely on a deidentified data set that includes the actual consent choices and other attributes of 12,444 patients who visited 186 medical providers in western New York. The data set has been provided by HEALTHeLINK, the HIE for western New York.

Contrary to common belief, we observe that once given a chance to make a decision about privacy, patients do not always follow the recommendation of their physicians but rather carefully consider the risks and benefits of providing consent. For patients, the number of physicians involved in their medical care, volume of medical records on the HIE, and the interaction between these two are positively associated with the likelihood of providing consent. On the other hand, the existence of medical records related to stigmatized conditions, such as behavioral health issues and mental illness, reduces the likelihood of providing consent.

We show that provider decisions to ask for consent are primarily motivated by the potential benefits of the HIE for themselves and their patients rather than by the potential financial risks associated with the HIE that medical providers may face due to patient migration to other providers.

While only a quarter of HIEs in the US consider themselves financially sustainable and cite privacy concerns as a major impediment to their growth (Rudin, Motala, Goldzweig, & Shekelle, , 2014; Karen

et al., 2016), due to strong local and state level support, HEALTHeLINK has overcome the privacy concerns of the patients and is financially sustainable. Despite the success of this platform, the majority of the remaining HIEs in the country are still struggling with this issue and are striving to persuade patients to provide consent so that they can increase their value proposition to their members and eventually become financially sustainable (Tripathi, Delano, Lund, & Rudolph, 2009; Adler-Milstein, Bates, & Jha, 2013; Kho et al., 2015). Therefore, the findings of this research have significant managerial implications for the majority of HIE platforms in the country that still have low patient participation levels due to privacy concerns.

The rest of this paper is organized as follows. Section 2 reviews the research on information technology and privacy within, respectively, the health economics and information systems literatures. This section also describes the HIE setting of the current study. Section 3 describes the variables in our model, sets out the empirical background, and presents our hypotheses. Section 4 develops our conceptual model and Section 5 presents the empirical results. Finally, Section 6 concludes the paper with a discussion on the theoretical and practical implications of our findings.

2 Related Work and Current Focus

Widespread adoption and use of health information technologies (HIT) is estimated to reduce the costs of health care services by $371 billion per year (Hillestad et al., 2005). Given these potential benefits, the federal government has invested as much as $26 billion dollars to incent the adoption and use of various HIT applications in the health care sector (Agha, 2014). The findings of studies on the impact of such investments are not consistent; while some have observed significant improvement in quality and efficiency (Javitt, Rebitzer & Reisman, 2008; McCullough, Casey, Mosocovice & Prasad, 2010; Miller & Tucker, 2011a), others show modest (Borzekowski, 2009) or no improvements at all (Agha, 2014; DesRoches et al., 2010; Furukawa, Raghu & Shao, 2010). Researchers have also examined the drivers of HIT adoption and exchange of health information. Miller and Tucker (2014) show that unlike other two-sided platforms, focusing on large, marquee users is not an optimal strategy for attracting smaller users to HIE platforms. This is consistent with earlier studies that show that the effects of scale on hospitals' decisions to adopt HIT diminishes over time (McCullough, 2008). On the other hand, stricter state regulations on privacy and the existence of rules that facilitate the use of electronic medical records in courts are shown to impede HIT adoption and exchange of health information (Miller & Tucker, 2009, 2012).

A recent stream of research focuses on privacy antecedents by investigating how individuals make privacy decisions and by examining the factors that lead them to disclose their personal information. Researchers have studied the role of emotions (Anderson & Agarwal, 2011), uncertainty (Pavlou, Liang & Xue, 2007) and information transparency (Awad & Krishnan, 2006). Despite notable exceptions (Anderson & Agarwal, 2011), previous research examines privacy in the broad context of online disclosure of either personal or financial data and does not examine how privacy concerns of individuals shift when it comes to medical data. Furthermore, the distinctive features of HIEs add to the complexity of the privacy decision-making process and consequently necessitates a careful examination of patients' consent choices on HIE platforms. Regardless of these differences, our understanding of the antecedents and outcomes of privacy in HIE settings is limited to few studies on the impact of privacy regulations on the development of HIEs (Adjerid, Acquisti, Telang, Padman & Adler-Milstein, 2015) and the association between patients' characteristics and their consent choices (Yaraghi, Sharman, Gopal, Singh, Ramesh, 2015). In addition, previous work is exclusively focused on individuals as the only decision makers and does not examine how others may influence such decisions. In this regard, the principal contributions of our research are twofold. First, the study analyzes actual privacy decisions made by patients in the context of an HIE and uncovers the factors underlying their choices. Second, and more importantly, we not only study the influence of physicians' recommendations on patients' decisions, but also examine the process through which this effect takes place.

In particular, the following contributions distinguish this research from our previous research (Yaraghi, Sharman et al., 2015) on patient consent. First and foremost, in the current research, we develop a theoretical framework that explains the interaction of patients and physicians and describes how these two parties consider their risks and benefits to make a decision regarding giving and asking for consent. However, our previous research was exploratory and hence did not provide a theoretical framework. Second, given the theoretical development in this paper, the number of variables included in the models is larger, while in our previous research, the variables were mostly limited to patients' demographics. While in this research we examine the variables related to the cost and benefits of asking for and providing consent, from the standpoints of both physicians and patients, our previous research limited the variables used in the model to patient demographics, and only included patients' age, gender, the complexity of their medical conditions, and whether a primary care physician was involved in their care. The richer theory and larger set of variables in the current research allowed us to shed more light on the decision-making process and provide specific policy recommendations and strategies to increase consent. This was not a possibility in our prior research mainly because the demographic variables were fixed and could not be easily changed to affect any outcome. Third, the theory and operationalization of a larger number of variables allowed us to focus on the process of decision-making, while, previously, we only examined the outcome of this process. That is, in previous research we examined the effects of the above-mentioned factors on the likelihood that a patient would provide consent, while in this research, we model a sequential process, allowing us to also examine the effect of physician-related factors on the likelihood of providing consent. Fourth, in this research, we examine the role of physicians in the sequential process of decision-making; in contrast, the role of physicians in this process was not adequately considered in the previous research because it was limited to a binary variable indicating if a primary care physician was involved in the care process of the patient. Finally, our empirical analysis in the current research includes multiple models and is significantly more robust than previous research. While in the current research, we implement bivariate and zero-inflated models to respectively account for the sequential nature of the process and the role of physicians in asking for consent, our prior research implemented only a logistic equation that examined the role of a limited set of variables on the likelihood of consent.

2.1 Setting

In this study, we analyze the consent choices of patients in western New York using deidentified data that are provided by HEALTHeLINK, the HIE of western New York. This HIE was created as a collaborative effort among community health care providers, large hospital systems, major laboratories and radiology centers, and regional health care payers. Currently, physicians can access the HIE to download the medical records that are created by major medical data providers. Such providers include the entire laboratories, imaging centers, and hospitals in the region, thus creating three types of medical data: laboratory reports, radiology reports, and hospital transcriptions. Although the medical data of patients are available on the HIE, they are not accessible to members without patients' explicit consent. The state of New York requires HIEs to implement an opt-in policy and obtain the consent of patients before sharing their medical records with their members. Patient consent is acquired at the offices of participating physicians. Patients can either allow physicians to have complete access or deny all physicians access to their medical records under any circumstance. Within each of these two choices, patients can further exclude

certain physicians. That is, patients can disclose their medical records to every HIE member except certain physicians, or disclose their records to no one, except in a medical emergency. This format effectively gives patients full control over who can access their records. The consent database used in this study only shows whether a patient has allowed or denied access to his medical records and does not specify if some physicians were excluded.

There is no restriction on the number of times that a practice can ask a patient for consent. However, once a practice asks for consent, practices must record the patient's decision. Although patients can change their consent decision anytime they wish, practices rarely ask the patient to make another decision once the patient has made an initial decision. We can identify the number of times that a practice has asked for the consent of a patient in our data set by looking at the number of times that the consent type has been updated. In our data set, of 12,444 patients, only 813 (6.5%) of patients have been asked more than once to provide consent, and of these, only 63 (0.5%) patients have changed their consent type.

3   Theoretical Framework

In this section we use a calculus perspective of information privacy—similar to what has been previously used to examine privacy decisions in other contexts such as GPS enables mobile services (Xu, Teo, Tan & Agarwal, 2009) and e-commerce (Dinev & Hart, 2006)—to describe the rationale on why various characteristics of medical practices and patients should affect their decision to ask for and provide consent to sharing records on an HIE, respectively.

Another closely related theoretical framework to our research is communication privacy management (CPM) theory. It was first proposed by Petronio (1991) to explain how people manage their privacy across interpersonal, family, and health communication contexts (Griffin, 2006, p. 170). According to CPM, people believe that they own their private information (Braithwaite, 1991) and set personal rules to control it. When an individual discloses his private information to others, the recipients also become co-owners of that information, and the co-owners together negotiate mutually agreeable privacy rules for the shared information. If this negotiation does not happen properly, or if co-owners fail to follow the new rules, boundary turbulence is the likely result. CPM argues that five factors are influential in forming the privacy rules: culture, gender, motivation, context, and risk/benefit ratio. The value of privacy and individualism in the cultural background of individuals affects the extent to which they disclose private information (Lowry, Cao, & Everard, 2011). Prior research shows that, as compared with females, males are generally more pessimistic about the ramifications

of private information disclosure (Petronio & Martin, 1986) and are less likely to disclose emotional information to family members and friends (Papini, Farmer, Clark, Micka, & Barnett,, 1990). Petronio (1991) argues that interest in or attraction to certain people can lead an individual to loosen privacy boundaries. The contextual factors refer to traumatic events, such as the diagnosis of AIDS and other stigmatized medical conditions, the loss of a limb and physical paralysis that may dampen the effects of other four factors (Griffin, 2006, p. 171). The cost/benefit ratio refers to the similar mental calculations that both social exchange theory (Emerson, 1976; Homans, 1958) and privacy calculus theory (Dinev & Hart, 2006) claim that individuals make before establishing relationships with others and disclosing information to others, respectively. According to this criterion, individuals set their privacy boundaries by evaluating the risks of disclosing private information against its benefits.

Note that the emphasis of this research is on the process of decision-making and the interplay between the utility functions of patients and providers. That is, our main focus in on the form of the utility functions rather than their input variables. In Section 4, we develop an econometric model using these functions to examine the process of privacy decision-making.

Within this framework we discuss the risks and benefits of obtaining and proving consent from the perspective of both medical practices and patients. While, for patients, information disclosure and providing consent to share medical records on an HIE is a privacy decision, for medical practices, asking patients for their consent can be better interpreted as an adoption decision. The difference in terminology (privacy vs. adoption) arises from the fact that patients have to decide if they want to disclose some of their privately held medical information while practices have to decide whether to encourage their patients to do so. When a practice asks a patient for consent, it does not disclose any of its own private information, but rather it encourages another agent (the patient) to do so. A patient's decision to provide consent will allow the medical practice to effectively adopt the HIE, which will provide some benefits to medical practices while also exposing patients to certain risks. We discuss these risks and benefits next.

3.1   Patients' Benefits from Providing Consent to Share Records on an HIE

HIEs enable physicians to easily access the medical records of their patients and thus helps them to order fewer redundant procedures and make better medical decisions (Ayabakan, Bardhan, Zheng, Kirksey, 2017; Yaraghi, 2015). These outcomes would directly benefit

patients, as they would receive higher quality of medical services at a lower cost. However, these benefits are not homogenously distributed among all patients; by allowing their records to become accessible through an HIE, those patients that have more medical records available on the HIE could benefit more from the platform as compared to patients with fewer records. This is due to the fact that patients with more medical records incur a higher cost for providing physicians with access to their records through alternative channels; without HIEs, such patients must either personally obtain hardcopies of their medical records and provide them to their physicians, or they must ask their providers to request previous medical records directly from other providers. Medical records that are shared on hardcopies by patients themselves or through fax or mail are often incomplete, difficult to interpret, and prone to errors (Shortliffe, 1999; Varon & Marik, 2002). Obtaining medical records through such alternative channels is not only expensive and inconvenient for patients (Ozcan & Kazley, 2008) but also exposes them to the risks that arise from practicing medicine based on incomplete and incorrect medical histories. The inconvenience of receiving services through conventional channels is a driver for adopting new service channels (Boyer, Hallowell, & Roth, 2002; Xue, Hitt, & Chen, 2011). Since sharing records on paper is more difficult for patients who have a higher number of medical records, they will benefit more from consenting to share their medical records on HIE as a more convenient alternative.

Hypothesis 1.1: An increase in the number of a patient's medical records leads to an increase in the likelihood of providing consent.

When multiple physicians are involved in the medical care of a patient, the patient has to provide all of them with access to his or her medical records. As the number of different physicians who are involved in the care process of the patient increases, the complexity of sharing hardcopies also increases, and, hence, the benefit to the patient derived by consenting to share medical records on an HIE increases as well. In cases where physicians do not have access to prior medical records, they are more likely to repeat medical procedures (Ayabakan et al., 2017; Eftekhari, Yaraghi, Singh, Gopal, Ramesh, 2017). Normally, the costs for such unnecessary procedures are a burden on patients. Therefore, patients who visit multiple physicians are likely to be more willing to provide consent to reduce the costs associated with reexamination.

Hypothesis 1.2: An increase in the number of a patient's medical providers leads to an increase in the likelihood of providing consent.

So far, we have argued that the benefits of HIEs are more salient for two groups of patients: those patients who have more medical records and those who have more physicians involved in their care. Note that these two groups are not necessarily the same. Certain patients may have many records but visit few physicians; similarly, some patients may have relatively few medical records but receive medical care from many physicians. Patients who benefit the most from HIEs are those who have both a large number of records and many physicians involved in their medical care. As such, these patients will stand to gain the most benefits from consenting to share their medical records on an HIE.

Note that patients who have more medical records and visit more physicians, are much more likely to be sicker and, consequently, to require more substantial medical care. Therefore, both the number of medical records and the number of physicians involved are factors that are likely to be confounded by the severity of the medical condition, in that interaction between these two variables can typically be viewed as measures of the overall health condition of a patient. Since one of the functionalities of HIEs is to provide instant access to medical records, the potential benefit derived from consenting to share medical records on an HIE increases along with the patient's demand for medical care.

Hypothesis 1.3: The number of medical providers moderates the relationship between the number of medical records and a patient's likelihood of consent such that when the number of medical providers is lower the association between the number of medical records and the likelihood of consent is weaker than it is when the number of medical providers is higher.

3.2 Patients' Risks from Providing Consent to Share Records on an HIE

There is substantial evidence in the medical literature that shows that social attitudes toward patients with mental illness have worsened over the past two decades (Angermeyer Matschinger & Schomerus , 2013), and disclosure of medical data may have emotional or reputational risks for patients with mental illnesses. For example, psychiatric patients may be stigmatized by society (Link, 1987), friends and family members (Moses, 2010) and even health care providers (Arvaniti et al. 2009). By providing consent and allowing medical providers to have access to their medical histories, patients with mental illnesses and behavioral health issues will expose themselves to risks of being stigmatized and may even receive lower quality care from medical providers who may be biased against such conditions.

While breach of medial data could lead to emotional and even medical hardships for certain patients, in the US context at least, it rarely leads to employment and health insurance discrimination. Three federal laws protect employees against discrimination based on health status in the workplace (Title I of the Americans with Disabilities Act (ADA), 42 U.S.C. 12101 et seq., the Rehabilitation Act of 1973, 29 U.S.C. § 701 et seq., and the Family and Medical Leave Act, 29 U.S.C. § 2601 et seq). As such, employers are legally barred from using data from an HIE to discriminate against employees. Similarly, in the US, the Patient Protection and Affordable Care Act (ACA), (42 U.S.C. § 18001 et seq. 2010) makes it illegal to deny health insurance coverage or charge disproportionately higher premiums on patients with preexisting medical conditions.

In spite of these legal protections, however, patients, especially those with stigmatized medical conditions, may nevertheless worry about unsanctioned discrimination on the part of employers or health insurance companies, or the possibility of future discrimination, should current laws and protections change.

Hypothesis 2: Patients with stigmatized medical conditions are less likely to provide consent.

3.3 Providers' Benefits from Obtaining Consent to Share Records on an HIE

Unless the flow of information on HIEs is authorized by patients, HIEs will not substantially affect medical practices in any form. The risks and benefits of HIEs for practices will only be realized after a practice obtains the consent of a patient to release medical records on an HIE. While physicians may be reluctant to share the medical records of their own patients with others, they often do need access to medical records prepared by other medical providers for their patients (Yaraghi, Du, Sharman, Gopal, & Ramesh, 2013, Yaraghi et al.. 2013). Without HIEs, physicians either have to depend on their patients for the records of services provided elsewhere, or must allocate staff time to contact other medical providers and ask them to send the medical records. If patients were to provide consent on an HIE, medical practices could save the resources that otherwise would have been spent on retrieving the records from other providers (Wright et al., 2010). Note that this potential benefit of HIEs is only realized for those patients that have a history of treatment and medical procedures recorded by other providers. In cases where a patient does not have any prior records or a given physician is the patient's only provider, HIEs will be less beneficial. Therefore, medical practices who have a higher proportion of patients previously or currently treated

by other providers will benefit more from their patients consenting to share medical records on an HIE and, hence, are also more likely to encourage their patients to do so.

Hypothesis 3.1: Medical providers who treat a larger number of patients previously or currently treated by other providers are more likely to ask patients for consent.

As discussed before, the availability of alternative channels has a strong influence on the potential value of HIEs as a means of accessing patients' medical records. If medical practices could access patient records through other channels, HIEs would be of less value to them, and, thus, they would have less incentive to ask their patients to provide consent. Proximity to main data providers offers easier and faster access to medical records for practices in dense urban areas compared to those in rural areas. As Vest and Gamm, (2010) note "HIE transactions could be especially important in support of rural patients, physicians, and hospitals who need the clinical information associated with rural patients' visits to urban specialists or hospitals. Such information can ensure effective management when such patients return to the care of their local provider." Moreover, to coordinate care, medical practices have to allocate substantial time and effort to search and obtain previous medical records of their patients through phone, fax, email, or mail (Hendrich, Chow, Skierczynski & Lu, 2008). HIEs significantly reduce efforts required for care coordination by streamlining this process and increasing its efficiency (Frisse et al., 2012; Hendrich et al., 2008). Since practices in rural areas tend to be smaller with fewer human resources, this feature of HIEs will be much more crucial and beneficial for them, as compared to their urban counterparts, because HIEs could free up relatively larger proportions of overall organizational resources.

On the other hand, practices in rural areas may already have the health records of the vast majority of their patients. If they do not share patients with other practices, they would not need to use HIEs to download other records or further coordinate care with other practices. Thus, the potential benefits that medical practices in rural areas would gain from patients' consent to share their records on an HIE would be capitalized in practices that share a considerable number of patients with others.

Hypothesis 3.2: The location of medical providers moderates the relationship between the number of patients transferred from other providers and the provider's likelihood of asking for consent, such that when a provider is located in an urban setting, the association between the number of transferred patients and the likelihood of asking

for consent is weaker than it is when the provider is located in a rural setting.

As with other types of information systems, a user's knowledge of the HIE system and its benefits gradually improves over time as the user gains more experience. Previous research (Yaraghi, Du, Sharman, Gopal, Ramesh, 2015) illustrates that medical practices become more efficient in using HIEs as they learn more about it over time. In addition to the learning effect, practices that have longer experiences with HIEs are those that have adopted HIEs sooner. Such practices tend to be more technologically savvy and organizationally ready and have more positive attitudes and opinions about HIEs and therefore benefit more from their patients' consent to share their records on an HIE as compared to practices that have adopted an HIE more recently and have less experience with it.

Hypothesis 3.3: The tenure of a medical provider with an HIE increases the likelihood of asking for consent.

3.4 Providers' Risks from Obtaining Consent to Share Records on an HIE

Despite the significant benefits of HIEs for patients, some medical providers may prefer not to share records of their patients with their peers. As other service providers, medical practices also compete with each other for patients and do not want to lose them to other medical providers. Restricting access to medical records is a very effective way to retain patients and inhibit them from migrating to other providers. According to the estimates of Baker, Bundorf, & Kessler (2015), in states where it is easier and cheaper for patients to obtain their medical records, the proportion of patients who switch their primary care physicians and specialists increases by 11% and 13%, respectively. Prior research identifies competition among medical providers as a barrier for their engagement in HIEs (Desai, 2014) and shows that providers who are more competitive, such as for-profit hospitals and those with smaller market shares, are much less likely to engage in HIE efforts (Adler-Milstein & Jha, 2014). Hence, medical practices located in more competitive markets may be more inclined to more tightly control their patients' medical records in order to dissuade them from seeking service from other providers within the same medical specialty. Since HIEs eliminate providers' strategic control over their patients' medical records, those who practice in more competitive areas face higher risks of losing their patients to other competitors and are may be less likely to encourage their patients to provide consent.

Note that the HIE in this study, HEALTHeLINK, provides its services to medical providers free of charge because it is funded by local and state governments. Thus, medical practices do not bear any direct financial costs from using the HIE.

Hypothesis 4: Medical providers who are located in more competitive markets are less likely to ask for consent.

4 Conceptual Framework

We develop a bivariate probit model to analyze the effects of the above-mentioned factors on the decisions of medical practices and patients to, respectively, ask for and provide consent. Poirier (1980) first introduced this model to provide a utility-maximizing rationalization for binary choice problems where the observed binary outcome does not reflect the choice of a single decision maker, but rather the binary joint choices of two decision makers. That is, two agents engage in a sequential decision-making process in which the decision of the second agent depends on that of the first agent and is only observed if the first agent makes a certain type of decision. A classic example is provided by Gunderson (1974), who estimates the probability that an employer retains a trainee after the completion of the training program. In this scenario, the employer first has to decide whether or not to offer a job to the trainee and then the trainee has to decide whether or not to accept the offer. The final outcome is a function of the preferences of two different agents; however, we do not observe the decisions of each agent separately, but rather only observe if the trainee is hired. In this case, even if the two decisions were independent, the outcome variable could not be correctly be assumed to have a univariate probit distribution. Another example is provided by Boyes, Hoffman, & Low (1989), who estimate the probability of loan defaults assuming that the bank and the individual engage in a sequential decision-making process in which the bank first decides whether to provide a loan to a customer and then the customer decides whether to default on the loan. In this case, we can observe the customer's decision only if the bank decided to provide the loan. The same model was later used by Greene (1992) to estimate the probability of default on credit card loans. More recently, such models have been applied in a wide variety of contexts, from detecting corporate fraud (Khanna, Kim & Lu, 2015; Wang, Winton & Yu, 2010) and measuring the spillover benefits of homeownership (Coulson & Li, 2013), to analyzing the benefits of insurance on health expenditures (Galárraga, Sosa-Rubí, Salinas-Rodríguez & Sesma-Vázquez, 2010) and estimating the demand for subsidized childcare (Wrohlich, 2008). Following the notation of Greene, (2000, p. 849) we define the utility functions of the medical practice and the patient from, respectively, asking for and providing consent as follows:

$$y_1{}^* = \boldsymbol{\beta'_1 x_1} + \epsilon_1, \qquad (1)$$

$$y_2{}^* = \boldsymbol{\beta'_2 x_2} + \epsilon_2 \qquad (2)$$

Where y_1^* and y_2^* are the latent utility functions of the practice and the patient and x_1 and x_2 are the vectors of covariates that defined the respective utility functions. A practice will ask for consent only if $y_1^* > 0$. That is:

$$y_1 = \begin{cases} 1 & \text{if } y_1^* > 0 \\ 0 & \text{otherwise} \end{cases}, \qquad (3)$$

Similarly, a patient will provide consent only if $y_2^* > 0$. As discussed before, the consent process is initiated by the medical practices. Therefore, if a medical practice does not ask a patient for consent, the choice of the patient will remain unknown. In our data set, the choice of the patients in such cases is shown by u and thus we observe three types of patient consents.

$$y_2 = \begin{cases} 1 & \text{if } y_1^* > 0 \ \cap y_2^* > 0 \\ 0 & \text{if } y_1^* > 0 \ \cap y_2^* \le 0, \\ u & \text{if } \ y_1^* \le 0 \end{cases} \qquad (4)$$

Assuming that the error terms in utility functions have a standard normal distribution and are correlated together with a covariance of ρ, we can define a bivariate normal cumulative distribution function for the joint distribution of ϵ_1 and ϵ_2 such that

$$\begin{bmatrix} \epsilon_1 \\ \epsilon_2 \end{bmatrix} \sim MVN \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right), \qquad (5)$$

That is,

$$\begin{aligned} &Prob(\epsilon_1 < X_1, \epsilon_2 < X_2) \\ &= \int_{-\infty}^{X_2} \int_{-\infty}^{X_1} \varphi(z_1, z_2, \rho) \, dz_1 dz_2 \end{aligned} \qquad (6)$$

in which $\varphi(z_1, z_2, \rho)$ is the bivariate normal distribution's density function. This allows us to define the probabilities of observing the three types of consents as following

$$\begin{aligned} P(y_2 = 1) &= P(y_1^* > 0 \ \cap y_2^* > 0) = \\ &P(\epsilon_1 < \boldsymbol{\beta}_1' x_1 \cap \epsilon_2 < \boldsymbol{\beta}_2' x_2) = \\ &\Phi(\boldsymbol{\beta}_1' x_1, \boldsymbol{\beta}_2' x_2, \rho) \end{aligned} \qquad (7)$$

$$\begin{aligned} P(y_2 = 0) &= P(y_1^* > 0 \ \cap y_2^* \le 0) = \\ &P(\epsilon_1 < \boldsymbol{\beta}_1' x_1 \cap \epsilon_2 < -\boldsymbol{\beta}_2' x_2) = \\ &\Phi(\boldsymbol{\beta}_1' x_1, -\boldsymbol{\beta}_2' x_2, -\rho) \end{aligned} \qquad (8)$$

$$\begin{aligned} P(y_2 = u) &= P(y_1^* \le 0) = P(\epsilon_1 < -\boldsymbol{\beta}_1' x_1) \\ &= \Phi(-\boldsymbol{\beta}_1' x_1) \end{aligned} \qquad (9)$$

The log-likelihood function will be simply derived as

$$\begin{aligned} \text{Log } \boldsymbol{\ell} &= \sum_{Consent=1} \text{Ln } \Phi(\boldsymbol{\beta}_1' x_1, \boldsymbol{\beta}_2' x_2, \rho) \\ &+ \sum_{Consent=0} \text{Ln } \Phi(\boldsymbol{\beta}_1' x_1, -\boldsymbol{\beta}_2' x_2, -\rho) \\ &+ \sum_{Consent=u} \text{Ln} \Phi(-\boldsymbol{\beta}_1' x_1) \end{aligned} \qquad (10)$$

Note that the bivariate probit model developed here is analogous to the seemingly unrelated regressions model except that the dependent variables are binary indicators (Chatla & Shmueli, 2017; Zellner, 1962).

In the next section, we provide the estimates of the above model along with a series of alternative models and robustness tests.

5 Empirical Analysis

In this section, we first describe the variables used. We then present our main results followed by robustness tests.

5.1 Variable Description

The dependent variable in our models is categorical. It is marked as "u" for unknown consent choices, equals 1 if the patient has provided consent, and 0 otherwise.

Based on our discussion in the prior section, we use the following independent variables in our model. Medical records show the number of unique records (laboratory reports, radiology reports, and hospital transcriptions) that are created over the two years prior to the date of consent and are available for each patient on the HIE database. Note that even if patients do not provide consent, their medical records are still available on the HIE; however, these records are not accessible to HIE members. For each patient, the number of involved physicians is equal to the number of unique physicians who have ordered medical reports for that patient. Stigma is a binary variable which is equal to 1 if the patient has a medical record created by a physician with a medical specialty in psychiatry and behavioral health.

Since physicians within the same medical specialty compete with each other over a limited number of potential patients in their locality, we measure competition using the Herfindahl-Hirschman index (HHI) based on the market share of physicians with the same specialty at the zip code level. To calculate the market share of each physician, we divided the number of patients seen by the physician by the total number of patients seen by other physicians with the same specialty and in the same zip code. Although some researchers use hospital service areas (HSAs) and hospital referral regions (HRRs) as groups of zip codes representing segments the health care market (Baker, 2001), we consider each zip code as a single market segment for two reasons. First, methods that group zip codes together and segment the market into larger units are appropriate for studies that use data sets from much larger geographical regions, such as states or the whole United States. By defining larger markets, these methods significantly reduce the variation in the data set and cannot adequately describe the microcompetitive behavior among providers in smaller local markets

(Sohn, 2002). This study is based on the much smaller geographical area of western New York and therefore using single zip codes as segments of the market allows us to study competition at microlevels between providers. Second, segmentation methods that group a large number of zip codes together are primarily designed to define markets for major and large providers such as hospitals. While hospitals treat patients across a large market, smaller medical practices treat patients from much smaller local markets concentrated in their close vicinities. Since our data set also includes small medical practices that compete with each other in local markets, single zip codes constitute much more appropriate market segments for calculating competition (HHI) for the purposes of this study.

To calculate the referrals for a specific physician, we created a social network in which nodes represent medical practices and directed links represent the flow of patients between them. In this network, the normalized in-degree centrality of a focal practice is calculated as the number of unique patients that had medical records created on the order of other medical practices prior to the date of consent. Tenure measures the number of months that a medical practice has been using an HIE. Finally, we control for the location of physician offices using an indicator variable, rural, which is equal to 1 if the zip code in which a physician practices is not classified as a core metropolitan area by United States Department of Agriculture.[1]

Our data set includes a sample of 12,444 patients who visited 186 medical practices in western New York. Of these patients, 965 (~7.8%) were not asked to provide consent and, therefore, their choice of consent is unknown and market with "u" in our data set. The remaining 11,479 patients were asked to provide consent—of these 709 patients (~6.1%) did not agree to do so. To ensure that the low percentage of observations with "unknown" or "no" consent types were not due to a clerical oversight or data entry error, we created a random sample of fifty patients who either did not provide consent or their consent type was marked as unknown. HEALTHeLINK verified that all of the consent types in the sample were correctly identified and there were no errors in data entry. The verification process involved comparing the archive of paper records on which consent was obtained with the electronic database in which consent type was indicated. A short description of the main variables is presented in Table A1.[2] Summary statistics along with correlations among of the variables are provided in Table A2.

5.2   Main Results

We use the NLMIXED procedure in SAS 9.3 to implement the maximum likelihood estimation method to fit our models. In order to better study the interaction terms and the effects of variables that pertain to two units (medical practices and patients), we standardized all continuous variables with a standard deviation of 1 around the zero mean.

We first run a simple probit model to estimate the probability that a medical practice asks a patient for consent. This is equivalent to estimating a probit model using the link function defined in Equation 9. In this model, the dependent variable is a binary and is equal to one if the final consent choice of the patient is either 1 or 0 and is equal to 0 if the final consent choice of the patient is unknown. In our data set, practices appear multiple times because each practice provides medical services to many patients. However, patient consent is rarely asked for more than once and those who were asked were extremely unlikely to change their consent type. Of the 12,444 patients, only 813 (6.5%) patients were asked more than once to provide consent; of these, only 63 (0.5%) patients changed their consent type. Due to the very small percentage of patients who changed their consent type, we pooled them all together and ignored patient-level fixed effects. To account for the unobservable factors that lead to potential correlation among the decisions of patients who visit the same practice, the standard errors of observations are clustered within each practice.

Column 1 of Table A3 shows the estimates of a model in which the utility of practices is only a function of practice benefits. While the practice benefits increase the likelihood of asking for consent, the risks, as captured by the level of competition (HHI), do not have any significant effect on reducing the likelihood of asking for consent. Column 2 shows the estimates when the patient-level characteristics are also added to the model. In both models, in-degree centrality is positive and significant, which confirms that practices that treat a greater number of patients transferred from other providers are more likely to ask their patients for consent. Interestingly, when we include patient characteristics in Column 2, the number of physicians involved and the interaction of this number with the volume of medical records are both positive and significant. That implies that medical practices consider patient benefits patients in their decision to ask for consent.

We then focus on the consent choice of the patients. If we simply remove the observations with unknown consent type from our data set, we can model the final

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[1] http://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/documentation.aspx

[2] All tables are located in the Appendix.

consent choice as a binary variable that is equal to 1 if the patient has provided consent and 0 otherwise. Note that these estimates are based on a limited data set from which 965 observations with unknown consent choices were removed, and thus only includes 11,479 observations with consent choices equal to either 0 or 1. Column 3 shows the estimates of a probit model in which the utility of a patient is only a function of patient characteristics, while Column 4 shows the estimates of a model that, in addition to patient characteristics, controls for practice characteristics. We observe that the number of medical records, physicians involved, and their interaction are all positively associated with the likelihood of providing consent while none of the practice characteristics are correlated with the final choice.

Finally, Columns 5 and 6 show the estimates of the bivariate probit model of Equation 10. Column 5 presents the estimates of a model in which the utility functions of practices and patients are driven by, respectively, practice and patient characteristics, while Column 6 shows the estimates of a model in which the utility of medical practices is a function of both patient and practice characteristics and, similarly, the utility of patients is also a function of both patient and practice characteristics. In both of the models, the covariance between the error terms of the two utility functions are estimated and shown as ρ, which in both Columns 5 and 6 is statistically insignificant, implying that there exists no unobserved factor that affects both patient and practice choices.

These models confirm our previous findings; practices, rural location and the ratio of patients with medical records created by other practices, as captured by in-degree centrality, are strongly associated with the likelihood of asking for consent. These variables represent the benefits to practices of obtaining patients' consent to share medical records on an HIE. On the other hand, potential risks, as captured by competition (HHI), have no statistically significant effect on reducing a practice's likelihood for asking for consent. The privacy decisions of patients follow a privacy calculus as well; patients with stigmatized medical conditions are less likely to give consent and those with a large number of medical records and involved physicians are more likely to do so. Most interestingly, while medical practices consider the benefits of their patients in their decision to ask them for consent, patients are not influenced by medical practices and, instead, make their privacy decisions based on an examination of their own risks and benefits.

5.3 Robustness Tests

Note that when a medical practice asks for patient consent, it does not mean that it necessarily "recommends" that patients give consent. To distinguish this difference, we consider a process in which the medical practice first makes its recommendation and then the patient makes the final choice. We estimate the probability of asking for consent as a proxy for the strength of the provider's recommendation to a patient for providing consent. This is based on the assumption that practices with higher probabilities of asking for consent are those that provide stronger recommendations for giving consent. In this process, the medical practice influences the patient by offering a recommendation, and the patient, in turn, considers this recommendation, along with personal factors, to reach the final consent decision. To capture this process, we modeled the utility of the patient as a function of patient characteristics, along with an estimated probability of asking for consent, as a proxy for the strength of the consent recommendation calculated for practices based on the estimates presented in Column 1. That is, we estimated a probit model in which the consent choice was a function of patient characteristics and one additional variable representing the strength with which a practice recommends consent. The values of his new variable (P), by definition, will be between 0 and 1 and can be interpreted as the level of effort that a practice invests in persuading a patient to provide consent. Including this variable in the model allowed us to examine how large the influence of medical practices is on patient consent decisions. Although the estimated P has a positive sign, it is not statistically significant and provides further confirmation of our main results that indicate that patients are not substantially driven by their physicians' recommendations and that, rather, they consider their own risks and benefits when deciding whether to share their medical records on an HIE.

To further check the robustness of our main results, we considered other estimation strategies. First, we replicated our main estimation models on a smaller stratified sample in which the ratio of "unknown" and "no consent" types were higher. Second, we transformed "unknown" consent types to "no consent" in order to construct a binary outcome and then estimated a zero-inflated binomial model using both probit and logit link functions to make sure that the estimates were robust even in the context of other function types. We discuss these strategies below.

In our sample, only a small percentage of patients were either not asked to provide consent or refrained from providing consent despite being asked to. These percentages, however, are still relatively high and do not qualify as a rare event in the context of our data set. King and Zeng (2001) define such data sets as those that have "dozens to thousands of times fewer ones (events, such as wars, vetoes, cases of political activism, or epidemiological infections) than zeros." More importantly, the problem of rare events concerns not so much the percentage of times an event happens as the overall number of cases. For example, an event with only a 2% chance of happening is considered rare in a

sample of 1000 observations because it only constitutes 20 events; however, in a sample of 10,000 cases, the same event with a 2% probability then happens 200 times and problem of underestimating the probability of the rare event is no longer an issue. In our case, the event of "no consent" has a relatively low chance of happening (~8%) however since we have a fairly large sample (N = 12,444), the frequency of this event is very high (N = 813). Therefore, our model parameters would not be overestimated. Even if we were dealing with a data set of rare events, only the intercepts would be overestimated and the slopes that test our hypotheses would remain consistent and unbiased.

Although the nonevents in our data are not significantly rare, we considered a conservative approach and conducted oversampling from our original data set to create a smaller data set with a higher percentage of no or unknown consent responses. To create the smaller sample, we first selected all of the observations with zero or unknown consent, and then randomly selected roughly 10% of the remaining observations with a consent equal to 1, stratified by the medical practice. The resulting data set includes the consent status of 2836 patients within 186 medical practices. Similar to the original sample, 965 (~34%) patients were not asked to provide consent and therefore their choice is unknown. From those that were asked to provide consent, 709 (~37%) patients did not agree to do so. Note that all of the 186 medical practices of the original data set also appear in the smaller data set and therefore the summary statistics of practice-level characteristics remain the same. Table A4 presents the summary statistics of the smaller data set and provides comparisons with the original data set. While the averages of the number of doctors, age, and stigma variables in the smaller data set are statistically different from those of the original data set, their differences are not economically significant. Table A5 presents the estimates of our models on the smaller data set. The estimates are similar in terms of (positive/negative) sign and significance to those that were based on the original data set, except that the estimates of stigma were negative, but not statistically significant. This is because we stratified our sample based on the dependent variable and since only a small proportion of patients in the larger sample had stigmatized conditions, our stratified sample includes an even smaller number of patients with such conditions and therefore the estimates of this variable become insignificant.

We can convert "u" consents to 0 and estimate a zero-inflated binomial model. As mentioned earlier in the paper, the state of New York has mandated an opt-in policy for HIE membership and, thus, unless patients explicitly provide consent, HIE members cannot access their medical records. That means that HIE members cannot access the records of patients with unknown consent—it is as if they had explicitly refused to provide

consent. Therefore, in practice, the "u" consent is similar to no consent because the records are, in either case, not accessible.

We therefore have a zero-inflated data set in which the zeros are the outputs of two binomial processes: either the medical providers did not ask for consent or patients refused to provide consent despite being asked by the medical providers. The 1s on the other hand only happen when medical providers ask for the consent and the patients agree to provide it. Following the notation of Section 4, assuming a probit link function, the probabilities of the two consent types will be as follows:

$$P(y_2 = 0) = 1 - \Phi(\beta_1'x_1) + \Phi(\beta_1'x_1)\big(1 - \Phi(\beta_2'x_2)\big) \tag{11}$$

$$P(y_2 = 1) = \Phi(\beta_1'x_1)\Phi(\beta_2'x_2) \tag{12}$$

And the log-likelihood function will be:

$$\text{Log } \ell = \sum_{Consent=0} \text{Ln} \left(1 - \Phi(\beta_1'x_1) + \Phi(\beta_1'x_1)\big(1 - \Phi(\beta_2'x_2)\big)\right) + \sum_{Consent=1} \text{Ln}\big(\Phi(\beta_1'x_1)\Phi(\beta_2'x_2)\big) \tag{13}$$

Similarly, if we use a logit link function, the log-likelihood function will be defined as follows:

$$\text{Log } \ell = \sum_{Consent=0} \text{Ln} \left[1 + \exp(\beta_1'x_1) + \exp(\beta_2'x_2)\right] - \text{Ln}(1 + \exp(\beta_1'x_1)) - \text{Ln}(1 + \exp(\beta_2'x_2)) + \sum_{Consent=1} \beta_1'x_1 + \beta_2'x_2 - \text{Ln}(1 + \exp(\beta_1'x_1)) - \text{Ln}(1 + \exp(\beta_2'x_2)) \tag{14}$$

We provide the estimates of Equations 13 and 14 in Table A6. Column 1 provides the estimates of a zero-inflated probit model in which the utilities of practices and patients are only a function of, respectively, practice and patient characteristics, and Column 2 shows the estimates of a zero-inflated probit model in which the utility functions consist of both practice and patient characteristics for both agents. The estimation results of the logit counterparts of these models are presented in Columns 3 and 4.

Table A7 summarizes the results of our hypotheses based on the estimates that we obtained from our main model and the three subsequent models that we ran as robustness tests. While the estimates are consistent in terms of (positive/negative) sign, their level of statistical significance varies across the models. This is primarily due to the fact that both the samples and the estimation methods are different. However, in all models we observe that in asking for consent, physicians assign significant weight to patient benefits, and in deciding whether to provide consent, patients take their own risks and benefits into account rather than merely relying on physician recommendations.

6   Conclusion

The percentage of hospitals that use an electronic health records (EHR) system grew from 9.4% in 2008 to 96.9% in 2014 (Charles et al., 2013). With the widespread adoption of EHRs, exchanging medical information has become more important than ever. HIE platforms are one of the most viable approaches for seamless exchange of medical information. Despite their potential, the success of HIEs hinges on the consent of patients. Without patient consent, HIEs cannot operate and, consequently, their potential to improve the quality and reduce the costs of health care will not be realized.   Therefore, it is critical to understand the factors that affect patients' choices and examine how patients make decisions about disclosing their medical information on HIEs. To the best of our knowledge, this research is the first study in this direction.

In this study we examine patients' decisions to disclose their medical records on HIE platforms and investigate the role of physicians in such decisions. Contrary to common belief, we observe that when given a chance to make a decision about their privacy preferences, patients do not merely follow the recommendation of their physicians but rather carefully consider the risks and benefits of providing consent. For patients, the number of physicians involved in their medical care, volume of medical records on the HIE, and the interaction between these two factors are positively associated with the likelihood of providing consent. On the other hand, the existence of medical records related to stigmatized conditions, such as behavioral health issues and mental illness, is negatively associated with the likelihood of providing consent. Our research shows that medical providers do not refrain from exchanging health information due to fear of losing their market share to their competitors. We show that provider decisions to ask for consent are positively associated with the potential benefits of the HIE for themselves and their patients rather than the financial risks of the HIE that medical providers may face because of patients' potential migration to other providers.

6.1   Policy Implications

The results of this research yield clear directions for focusing efforts on increasing the level of patient participation in HIE platforms so that such platforms can become effective tools in large-scale health care management. These directions are in direct consonance with the ongoing national efforts to improve the health care system in the US. If patients were to agree to disclose their medical information on HIE platforms, health care providers could provide better care and avoid medical redundancies, which would ultimately result in lowering the overall cost of healthcare services. Encouraging patients to provide consent and participate in HIE initiatives would be a critically important first

step in implementing such improvements. The model developed in this paper explains the privacy concerns of patients and their subsequent consent choices. As such, our model could help focus policy efforts concerning patient education and community awareness on the utility and value HIE platforms in public health. The results of this study could also direct these efforts toward specific target populations in need of such interventions.

The results of this study will also be of significant interest to HIE platforms seeking to enhance their value propositions to their participating members. The volume of accessible data on HIE platforms is directly proportional to the percentage of patients who provide consent. Therefore, the insights of this paper could also be applied in designing effective marketing strategies to enhance the level of consent among patients, ultimately increasing the value of an HIE to its members.

6.2   Limitations and Future Work

Given data limitations, some important variables are not included in our models. For example, peer pressure, which could be a strong driver of patient consent, is not included in this study. There are multiple unobserved confounding factors that may explain the correlation between different practice- and patient-level characteristics and the final disclosure decision. Without controlling for these factors, the reported coefficients might be endogenous. For instance, one such unobserved factor is the severity of the patient's illness. This factor may explain multiple relationships observed in the data, including the positive effect of a patient's age and the number of doctors involved in his or her care on the patient's decision to disclose information on the HIE. As we discussed in Section 3.1, it is possible that patients with more severe illnesses are more likely to see multiple physicians, and also more likely to be willing to share their medical records. As such, it is possible that the relationship between number of physicians and the willingness to disclose may be coincidental rather than causal. This limitation could be overcome by controlling for risk-adjustment index based on Elixhauser comorbidities. We were not able to implement this method because diagnosis codes are recorded in EMR systems at the practices and were not available on the HIE we used. Future analysis of more granular data could shed more light on patient privacy decisions.

We also observe that some patients were asked for their consent multiple times. Such patients may provide consent eventually. The number of times that a patient is asked to provide consent could be considered as a proxy for the pressure. It would be interesting to examine if and how such pressure could lead patients to provide consent, as this information could help design efficient processes to obtain patient consent.

Another potential for future research could be a nationwide comparison of privacy decisions among different HIEs. As we discussed earlier in the paper, HEALTHeLINK is quite successful compared to other HIEs, as a significantly higher percentage of medical providers than typical have adopted its services and, due to its local marketing efforts, a considerable portion of patients have agreed to disclose their medical records (Holmgren, Patel, & Adler-Milstein, 2017). This is partly due to the fact that HEALTHeLINK has received strong support from state government, local insurance companies, and regional medical providers. Unlike the majority of HIEs, HEALTHeLINK is financially visible (Adler-Milstein et al., 2016). Additionally, HEALTHeLINK operates in a market with unique privacy regulations. Unlike many other states, New York has adopted an opt-in policy requiring HIEs to obtain explicit consent from patients before sharing their records. In states that have implemented an opt-out policy, the dynamics of decision-making may be very different. Given these differences in the HIE itself and the conditions of the market in which it operates, the results of this study may not be generalizable to other HIEs.

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Appendix

Table A1. Description of the Main Model Variables

Variable		Description
Medical practice characteristics	Tenure	Number of months since HIE adoption
	Rural	The location of the medical practice, which is equal to 1 if it is rural and 0 otherwise
	HHI	Herfindahl-Hirschman index calculated using the market share of physicians with the same specialty at the zip code level. To calculate the market share of each physician, the number of patients seen by the physician is divided by the total number of patients seen by other physicians with the same specialty and in the same zip code.
	In-degree centrality	Normalized in-degree centrality of a practice in the network of common patients
Patient Characteristics	Records	The number of medical records available on the HIE at the time of consent
	Physicians	The number of different physicians who have ordered medical reports for a patient up to the time of consent
	Stigma	= 1 if patient has a medical record ordered by a psychiatrist or a behavioral health specialist
	Age	Age of the patient in years
	Male	= 1 if patient is male and 0 otherwise

Table A2. Summary Statistics

	Mean	S.D.	Tenure	Rural	HHI	In-degree centrality	Medical records	Doctors	Stigma	Age
Tenure	27.0826	3.1786								
Rural	0.1677	0.3736	0.15216 < .0001							
Competition (HHI)	51.1498	67.0600	0.14813 < .0001	-0.55071 < .0001						
In-degree centrality	0.1799	0.0521	0.19938 < .0001	0.62458 < .0001	0.46275 < .0001					
Medical records	5.9793	13.8980	0.00155 0.8626	-0.04307 < .0001	0.02687 0.1525	-0.04421 < .0001				
Doctors	0.9268	1.1200	-0.01344 0.1338	-0.02865 0.0014	-0.08189 < .0001	-0.04732 < .0001	0.37027 < .0001			
Stigma	0.0032	0.0573	-0.04020 < .0001	-0.02581 0.0040	-0.05557 0.0031	-0.12304 < .0001	0.02107 0.0187	0.02379 0.0080		
Age	50.5354	22.7844	0.01274 0.1551	0.01560 0.0818	-0.08026 < .0001	0.06129 <.0001	-0.00797 0.3740	0.10702 < .0001	-0.03237 0.0003	
Male	0.3558	0.4787	0.08165 < .0001	0.02757 0.0021	-0.01108 0.5553	0.09249 < .0001	0.01623 0.0703	0.04198 < .0001	-0.00173 0.8473	0.06977 < .0001

Table A3. Consent Choice (Probit Model in Original Data Set)

	Variable	Model					
		(1)	(2)	(3)	(4)	(5)	(6)
Covariates of practice utility function (x_1)	Intercept	**1.4944*** (0.0241)**	**1.5064*** (0.0273)**			**1.4941*** (0.02418)**	**1.5063*** (0.02738)**
	Tenure	0.0106 (0.0167)	0.0102 (0.0168)			0.01008 (0.01678)	0.00998 (0.01681)
	Tenure2	-0.0248** (0.0116)	**-0.0273** (0.0116)**			**-0.02418** (0.01168)**	**-0.02777** (0.01166)**
	Rural	**0.2040*** (0.0732)**	**0.1913*** (0.0740)**			**0.2028*** (0.07365)**	**0.1914*** (0.07404)**
	Competition (HHI)	-0.0236 (0.0218)	-0.0117 (0.0220)			-0.02363 (0.02181)	-0.01255 (0.02218)
	In-degree centrality	**0.2087*** (0.0213)**	**0.2041*** (0.0217)**			**0.2088*** (0.02139)**	**0.2043*** (0.02176)**
	In-degree centrality × Rural	0.0430 (0.0511)	0.0237 (0.0524)			0.04514 (0.05123)	0.02426 (0.05253)
	Medical records		0.0297 (0.0239)				0.03138 (0.02399)
	Doctors		**0.0226** (0.0193)**				**0.04443** (0.01942)**
	Medical records × Doctors		**0.0226* (0.0118)**				**0.02437* (0.01240)**
	Stigma		0.0042 (0.0139)				0.004524 (0.01397)
	Age		**0.1058*** (0.0163)**				**0.1068*** (0.01637)**
	Male		-0.0102 (0.0358)				-0.00967 (0.03579)
Covariates of patient utility function (x_2)	Intercept			**1.5825*** (0.0244)**	**1.5781*** (0.0311)**	**1.6058*** (0.0434)**	**1.4914 *** (0.1387)**
	Medical records			**0.1021*** (0.0378)**	**0.1224*** (0.0406)**	**0.1016*** (0.0378)**	**0.09973** (0.04006)**
	Doctors			**0.1380*** (0.0267)**	**0.1338*** (0.0271)**	**0.1379*** (0.0258)**	**0.1271*** (0.03241)**
	Medical records × Doctors			**0.0137*** (0.00432)**	**0.0142*** (0.00436)**	**0.0136*** (0.0045)**	**0.01226** (0.005119)**
	Stigma			**-0.0267* (0.0155)**	**-0.0278* (0.0159)**	-0.0253 (0.0157)	-0.02341 (0.01591)
	Age			**0.2238*** (0.0182)**	**0.2144*** (0.0185)**	**0.2226*** (0.0185)**	**0.2291*** (0.01826)**
	Male			0.0604 (0.0403)	0.0473 (0.0412)	0.0586 (0.0403)	0.03978 (0.04056)
	Tenure				0.0117 (0.0208)		0.02086 (0.02047)
	Tenure2				0.0114 (0.0154)		0.01890 (0.01646)
	Rural				0.00656 (0.0936)		0.1865 (0.08087)
	Competition (HHI)				-0.0163 (0.0237)		0.01013 (0.02334)

					0.0183 (0.0293)		0.04628 (.05085)
In-degree centrality × Rural					0.0143 (0.0593)		0.06761 (0.05489)
P							
ρ						-0.1877 (0.3881)	0.3972 (0.4290)

Notes: ***p < 0.01, **p < 0.05, *p < 0.1.

Model 1: Estimates the probability that a practice asks for consent when only practice-level characteristics are included in the model. DV is equal to 1 if the final consent choice of the patient is known and is equal to 0 otherwise.

Model 2: Estimates the probability that a practice asks for consent when both practice and patient level characteristics are included in the model. DV is equal to 1 if the final consent choice of the patient is known and is equal to 0 otherwise.

Model 3: Estimates the probability that a patient agrees to provide consent when only patient level characteristics are included in the model. DV is equal to 1 if the patient has provided consent and 0 otherwise. These estimates are based on a limited data set from which 965 observations with unknown consent choices were removed.

Model 4: Estimates the probability that a patient agrees to provide consent when both practice and patient level characteristics are included in the model. DV is equal to 1 if the patient has provided consent and 0 otherwise. These estimates are based on a limited data set from which 965 observations with unknown consent choices were removed.

Model 5: Estimates the joint probability that a patient gives consent conditional on the practice asking for it using the bivariate probit model of Equation 10, in which the utility functions of practices and patients are exclusively driven by, respectively, practice and patient characteristics.

Model 6: Estimates the joint probability that a patient gives consent conditional on the practice asking for it using the bivariate probit model of Equation 10 in which the utility of medical practices is a function of both patient and practice characteristics and, similarly, the utility of patients is also a function of both patient and practice characteristics.

Table A4. Summary Statistics on Stratified Data Set and Comparisons with the Original Data Set

Variable	**Mean**	**Std. Dev.**	$H_0: \mu_l - \mu_s = 0$
Medical records	5.6513	9.8264	0.3281
Doctors	0.8766	1.0688	2.17**
Stigma	0.0063	0.0794	-2.37**
Age	46.5087	23.994	8.26***
Male	0.3434	0.4749	1.25

Notes: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A5. Consent Choice (Probit Model in Stratified Data Set)

	Variable	(1)	(2)	(3)	(4)	(5)	(6)
				Model			
Covariates of practice utility function (x_1)	Intercept	**0.4764*** (0.0341)**	**0.4773*** (0.0386)**			**0.4761*** (0.0341)**	**0.4776*** (0.0386)**
	Tenure	0.0334 (0.0248)	0.0310 (0.0249)			0.0341 (0.0248)	0.0308 (0.0249)
	Tenure2	**-0.0352* (0.0172)**	**-0.0359** (0.0173)**			**-0.0345** (0.0174)**	**-0.0365** (0.0173)**
	Rural	-0.1761 (0.1111)	0.1731 (0.1122)			0.1816 (0.1129)	-0.1739 (0.1123)
	Competition (HHI)	-0.0375 (0.0313)	**-0.0317 (0.0318)**			-0.0381 (0.0313)	-0.0324 (0.0319)
	In-degree centrality	**0.2473*** (0.0335)**	**0.2499*** (0.0341)**			**0.2476*** (0.0335)**	**0.2500*** (0.0341)**
	In-degree centrality × Rural	0.0358 (0.07613)	0.0072 (0.0776)			0.0380 (0.0765)	0.0078 (0.0777)
	Medical records		**0.0816** (0.0330)**				**0.0828** (0.0329)**
	Doctors		**0.1058*** (0.0289)**				**0.1056*** (0.0329)**
	Medical records×Doctors		**0.0406*** (0.0143)**				**0.0425*** (0.0145)**
	Stigma		0.0302 (0.0246)				0.0310 (0.0247)
	Age		**0.0445* (0.0249)**				**0.0452* (0.0249)**
	Male		-0.0191 (0.0525)				-0.0202 (0.0526)
Covariates of Patient utility function (x_2)	Intercept			**0.2971*** (0.0376)**	**0.2786*** (0.0479)**	**0.3332** (0.1430)**	0.1124 (0.2881)
	Medical records			**0.1201*** (0.0477)**	**0.1443*** (0.0497)**	**0.1200*** (0.0461)**	**0.1058* (0.05858)**
	Doctors			**0.1468*** (0.0379)**	**0.1420*** (0.0386)**	**0.1471*** (0.0366)**	**0.1258** (0.05544)**
	Medical records×Doctors			**0.0152** (0.0075)**	**0.0164*** (0.0075)**	**0.0152* (0.0078)**	0.01177 (0.01047)
	Stigma			-0.0057 (0.0293)	-0.00001 (0.0300)	-0.0069 (0.0298)	-0.01286 (0.0308)
	Age			**0.3132*** (0.0319)**	**0.2942*** (0.0323)**	**0.3125*** (0.0319)**	**0.3060*** (0.03483)**
	Male			**0.1236* (0.0644)**	0.1057 (0.0658)	**0.1221* (0.0647)**	0.09834 (0.06643)
	Tenure				0.0153 (0.0329)		-0.00409 (0.03333)
	Tenure2				0.0177 (0.0248)		0.03111 (0.02761)

Rural					0.0553 (0.1585)		**0.2662*** **(0.1372)**
Competition (HHI)					-0.0476 (0.0392)		-0.03500 (0.03868)
In-degree centrality					0.0293 (0.0458)		0.06969 (0.08741)
In-degree centrality×Rural					0.0127 (0.0941)		0.09926 (0.09081)
P							
ρ						-0.0662 (0.2553)	0.3137 (0.5093)

Notes: *** p < 0.01, **p < 0.05, *p < 0.1.

Model 1: Estimates the probability that a practice asks for consent when only practice-level characteristics are included in the model. DV is equal to 1 if the final consent choice of the patient is known and is equal to 0 otherwise.

Model 2: Estimates the probability that a practice asks for consent when both practice and patient level characteristics are included in the model. DV is equal to 1 if the final consent choice of the patient is known and is equal to 0 otherwise.

Model 3: Estimates the probability that a patient agrees to provide consent when only patient level characteristics are included in the model. DV is equal to 1 if the patient has provided consent and 0 otherwise. These estimates are based on a limited data set from which 965 observations with unknown consent choices were removed.

Model 4: Estimates the probability that a patient agrees to provide consent when both practice and patient level characteristics are included in the model. DV is equal to 1 if the patient has provided consent and 0 otherwise. These estimates are based on a limited data set from which 965 observations with unknown consent choices were removed.

Model 5: Estimates the joint probability that a patient gives consent conditional on the practice asking for it using the bivariate probit model of Equation 10, in which the utility functions of practices and patients are exclusively driven by, respectively, practice and patient characteristics.

Model 6: Estimates the joint probability that a patient gives consent conditional on the practice asking for it using the bivariate probit model of Equation 10 in which the utility of medical practices is a function of both patient and practice characteristics and, similarly, the utility of patients is also a function of both patient and practice characteristics.

Table A6. Zero-Inflated Binomial Model with Probit and Logit Link Functions

	Variable	(1)	(2)	(3)	(4)
Covariates of practice utility function (x_1)	Intercept	**1.7420*** (0.03192)**	**1.1757*** (0.02416)**	**3.2302*** (0.2777)**	**1.9504*** (0.04453)**
	Tenure	**0.5934*** (0.2016)**	0.005370 (0.01534)	**0.9620** (0.4262)**	0.01768 (0.02864)
	Tenure^2	**-1.4815*** (0.5160)**	-0.01321 (0.01145)	**-3.4343*** (1.2539)**	-0.02498 (0.02070)
	Rural	**1.1296*** (0.2591)**	0.07550 (0.06924)	**2.3667*** (0.5141)**	0.04918 (0.1228)
	Competition (HHI)	-0.6530 (0.4084)	**0.05572*** (0.02086)**	-0.8373 (0.9269)	0.02075 (0.3472)
	In-degree Centrality	**0.1884*** (0.04798)**	**0.1290*** (0.02067)**	**0.4431*** (0.1233**	**0.2339*** (0.03614)**
	In-degree Centrality×Rural	**1.2080*** (0.3007)**	**0.07676* (0.04576)**	**2.6933*** (0.8213)**	0.08945 (0.08284)
	Medical records		0.02676 (0.02252)		0.04745 (0.04325)
	Doctors		**0.03651** (0.01727)**		**0.05827* (0.03287)**
	Medical Records×Doctors		0.00127 (0.005645)		0.000281 (0.01335)
	Stigma		-0.00856 (0.01250)		-0.01564 (0.02120)
	Age		**0.1778*** (0.01425)**		**0.3432*** (0.02587)**
	Male		0.009092 (0.03119)		0.02554 (0.05778)
Covariates of patient utility function (x_2)	Intercept	**1.2696*** (0.02423)**	**21.3831*** (4.4048)**	**2.0556*** (0.04809)**	**155.67*** (29.7900)**
	Medical records	0.03572 (0.02556)	0.09786 (0.1698)	0.08272 (0.05134)	0.1866 (2.6986)
	Doctors	**0.03894** (0.01965)**	0.06185 (0.1809)	**0.07298* (0.03781)**	0.1996 (0.9372)
	Medical Records×Doctors	0.00313 (0.005017)	0.1596 (0.1796)	0.00626 (0.01034)	0.1454 (0.8208)
	Stigma	**-0.9845*** (0.001394)**	**-0.4698* (0.2543)**	-0.03327 (0.02570)	**-15.2001*** (1.7623)**
	Age	**0.1888*** (0.01617)**	0.09763 (0.1194)	**0.3600*** (0.02976)**	0.1470 (0.5364)
	Male	0.03192 (0.03407)	0.2429 (0.2863)	0.04405 (0.06346)	0.3177 (1.1601)
	Tenure		**3.5310*** (0.8219)**		**23.3177*** (4.5854)**
	Tenure^2		**-3.0446*** (0.6742)**		**-19.0081*** (3.6926)**
	Rural		**15.4776*** (3.1656)**		**105.21*** (21.7672)**
	Competition (HHI)		**-8.4527*** (1.8910)**		-0.4061 (1.5970)
	In-degree Centrality		**6.0845*** (1.3437)**		**33.9258*** (6.6038)**
	In-degree Centrality×Rural		**163.39*** (32.9371)**		**194.28*** (32.9978)**

Notes: ***p < 0.01, **p < 0.05, *p < 0.1

<p style="text-align:center;color:blue;font-weight:bold;">Table A7. Summary of Hypotheses Test Results</p>

Hypothesis	Model			
	Bi-variate probit on whole sample	*Bi-variate probit on stratified sample*	*Zero-inflated binomial (probit)*	*Zero-inflated binomial (logit)*
H1.1: An increase in the number of a patient's medical records leads to an increase in the likelihood of providing consent.	S	S	NS	NS
H1.2: An increase in the number of a patient's medical providers leads to an increase in the likelihood of providing consent.	S	S	PS	PS
H1.3: The number of medical providers moderates the relationship between the number of medical records and a patient's likelihood of consent such that when the number of medical providers is lower, the association between the number of medical records and the likelihood of consent is weaker than it is when the number of medical providers is higher.	S	PS	NS	NS
H2: Patients with stigmatized medical conditions are less likely to provide consent.	PS	NS	S	PS
H3.1: Medical providers who treat more patients transferred from other providers are more likely to ask patients for consent.	S	S	S	S
H3.2: The location of medical providers moderates the relationship between the number of patients transferred from others and the provider's likelihood of asking for consent such that when a provider is located in an urban setting, the association between the number of transferred patients and the likelihood of asking for consent is weaker than it is when the provider is located in a rural setting.	NS	NS	S	PS
H3.3: The tenure of a medical provider with an HIE increases the likelihood of asking for consent.	NS	NS	PS	PS
H4: Medical providers who are located in more competitive markets are less likely to ask for consent.	NS	NS	PS	NS
Notes: S: Supported with $p < 0.1$ NS: Not supported with $p < 0.1$ PS: Partially supported: Significant at $p < 0.1$ at either the main model or the model with controls.				

About the Authors

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