Understanding Contingencies Associated with the Early Adoption of Customer-Facing Web Portals

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Abstract: Web-based portals extend many convenient and collaborative capabilities to consumers and are being adopted by small firms with ever greater frequency, especially in the context of health care. The early adoption of patient portals by ambulatory-care clinics (outpatient health providers) presents a unique opportunity to more fully understand the characteristics of supply-side adopters in a context where firms (ambulatory-care clinics) are extending digital services to consumers (patients). Using diffusion of innovations literature and contingency theory as the theoretical base, we expand upon the firm characteristics traditionally considered to be predictors of adoption (e.g., firm size, slack resources, competition, capabilities, and management support) and examine how *demand contingencies, service contingencies,* and *learning externality contingencies* affect patient portal adoption by ambulatory-care clinics in the United States. We find that early adopters often have a structure in place that provides support for innovations (e.g., part of integrated delivery systems), as would be predicted by diffusion of innovation theory. We also find, though, that *service contingencies* associated with continuity of care, *learning externality contingencies* associated with local influences, and select *demand contingencies* associated with the local market significantly influence patient portal adoption decisions. Our findings suggest that the adoption and diffusion of patient portals may be affected by more than traditionally considered "dominant" firm characteristics and provide insights into how such customer-facing systems may be affected by contingent factors.

Key words and phrases: adoption of innovations, bivariate probit with sample selection, demand contingencies, factors of adoption, learning externality contingencies, patient portals, service contingencies, Web portals.

Clinical patient portals provide patients with Web-based access to medical records and often offer additional features such as collaborative disease management capabilities and patient–clinician e-mail/messaging [15]. While customer-facing, Web-based portals have become ubiquitous in other sectors—such as banking, travel, and retail—portal adoption in health care has been slow. Approximately 9 percent of surveyed medical practices (i.e., ambulatory-care clinics) in the United States had adopted some form of a clinical patient portal by 2010.[1] Recently, adoption rates of patient portals have been increasing as a result of policies directed toward health information technology (HIT), the demand for patient-centered care, chronic disease management concerns, and physician technology adoption incentives [8, 9]. This presents a unique opportunity to more fully understand the characteristics of early supply-side adopters of patient portals in a context where firms (ambulatory-care clinics) are extending collaborative, digital services to consumers (patients).

Transaction-oriented portals seen in other industries, such as online banking portals, e-commerce portals, and online travel portals, are often designed to increase customer convenience and reduce costs associated with physical service encounters. Patient portals, however, represent an opportunity for patients and clinicians to work together to achieve improved health outcomes through coordination of care, sharing of pertinent data and records, and continuous tracking of patient health indicators (e.g., blood-pressure and glucose levels) [65]. In addition, many other interesting factors make the adoption of patient portals by ambulatory-care clinics unique and make the study of supply-side adoption of patient portals an interesting research avenue for information systems (IS) researchers. Competition in the health-care industry, especially between ambulatory-care clinics, is typically local. Services provided by different specialized ambulatory clinics can be very diverse, and as a result, relationships with patients can range from one-time emergency visits to long-term repeated encounters and disease management. The type and amount of information associated with encounters with ambulatory clinics can be quite diverse and complex, especially given the local market focus and that resource and knowledge constraints are often distinct from those faced by large, centralized corporate entities. It is also interesting to note that despite competition at the local level, physician professional organizations and communities of practice often collaborate and learn from each other.

Traditional research on the adoption of innovative IS by firms suggests that the most frequent supply-side adopters of innovative IS are large organizations with plenty of slack resources, capabilities, and management support motivated by competition [21]. This is referred to as the "dominant paradigm" of the diffusion of innovations and is based on a long tradition of research in this area [21, 49]. However, as ambulatory-care clinics seek congruencies ("fit") with technological and environmental changes, managerial decision making related to patient portal adoption is likely to be affected by more than the size of the firm, the resources available, and competitive motivations. To our knowledge, though, contingent models have not been used to extend diffusion of innovations theory into the context of patient portal adoption by ambulatory-care clinics. Patient portals, in particular, represent an interesting nexus between supply-side services provided by ambulatory-care clinics and complex demand-side needs of patients who often possess long health histories.

In this study, we use contingency theory as a base to hypothesize how contingent factors, above and beyond the traditionally considered "dominant" factors often associated with supply-side adoption [21], may affect the adoption of patient portals by ambulatory-care clinics. Specifically, we examine how *demand contingencies* within the local market may favor or hinder adoption; how *service contingencies* associated with the type of relationship between the service provider and the patient may affect adoption; and how *learning externality contingencies* (where local physicians and practices learn and influence each other) may affect adoption of patient portals by ambulatory-care clinics within the United States. Specifically, we ask the following research question:

> *RQ: Do contingent factors (demand contingencies, service contingencies, and learning externality contingencies) influence the adoption of clinical patient portals by ambulatory-care clinics?*

Using a cross-sectional data set that merges adoption decision data reported by ambulatory-care clinics in the United States and county-level demand and wage data, we develop a sample selection model of supply-side adoption. We find partial support for the impact of *demand contingencies* on patient portal adoption and strong support for the impact of *service contingencies* and *learning externality contingencies* on patient portal adoption. Our findings suggest that the adoption of patient portals may be affected by more than traditionally considered "dominant" firm characteristics and provide insights into how contingent factors affect customer-facing Web portals.

The remainder of this paper discusses the research background, the development of our hypotheses and conceptual research model, the data and methods used to analyze ambulatory-care clinic adoption of clinical patient portals, results, and final thoughts in the discussion and conclusion sections.

Research Background

A CUSTOMER-FACING PORTAL is defined generally by Smith as "an infrastructure providing secure, customizable, personalizable, integrated access to dynamic content from a variety of sources, in a variety of source formats, wherever it is needed" [56, p. 94]. For the context of this study, we suggest that a *patient portal* is a Web-based application that provides online digital access to health-care services and information provided directly by an ambulatory-care clinic. Such patient portals often provide patients and providers with access to clinical information, patient records, communication capabilities, and collaborative disease management functionalities. *Ambulatory-care clinics* are "health services that do not require overnight hospitalization" [62, p. 129] and are growing rapidly in the United States because a significant amount of health services that used to require hospitalization, such as surgery, are now often performed in ambulatory-care settings. In this study, we focus on clinical patient portals tethered directly to ambulatory-care clinic electronic medical records (EMRs).

Diffusion of Innovations Theory and the "Dominant Paradigm"

Diffusion of innovations theory generally suggests that innovations diffuse in an S-shaped pattern beginning with innovators (a small percentage of very early adopters) and progresses through subsequent stages of increasing adoption rates until reaching a plateau [49]. A substantial amount of research has focused on diffusion of innovation patterns on the supply side and has resulted in a "dominant paradigm" [21]. The "dominant paradigm" refers to a large number of studies related to IS adoption that have shown that variance in the "quantity of innovation" is well known to be explained by increasing levels of organizational size and structure, knowledge and resources, management support, compatibility, and competitive environment [21, 35]. Such adoption and diffusion research, though, has primarily focused on the adoption of IS that improve the productivity and efficiency within firms. In terms of Swanson's [63] multicore model of firm adoption of IS, extant IS adoption research has predominantly focused on adoption of Type 2 IS *internal* to a firm (e.g., accounting IS) and Type 3 innovations that provide connections *between* loosely coupled firms (e.g., electronic data interchange [EDI] [34]). Even within the health-care context, theoretical health-care technology adoption frameworks [51] are primarily based on assessing adoption of innovative technologies that improve internal efficiencies of health-care providers and communication capabilities between providers.

Research considering what types of firms adopt *customer-facing information systems* is emerging (e.g., [13]) but is limited. Much of the existing research on supply-side adoption of innovative, customer-facing systems focuses on the context of transaction-based e-commerce. For instance, Chatterjee et al. [13] find that *top management championship, strategic investment rationale,* and *extent of coordination* all affect the assimilation (use and routinization) of Web technologies by firms. Hong and Zhu [33] find that *technology integration, Web spending, Web functionalities, EDI use, partner usage,* and *perceived obstacles* affect adoption of e-commerce technologies by firms. The technology acceptance model (TAM) and TAM hybrid frameworks have also been used to extract supply-side predictors of adoption within the context of managerial decision making [29]. We suggest that all these models, while controlling for differences such as the age of the firm and experience with Web technologies [13] and the size of the firm and industry type [33], do not fully consider the firm contingencies associated with managerial decision making. We next consider how a contingency-based model may help to explain many of the interesting nuances within the context of patient portal adoption by ambulatory-care clinics.

Contingency Theory and Its Impact on Adoption Decisions

Contingency theory suggests that managers have the ability to make strategic decisions in order to find an appropriate fit with shifting technological and environmental conditions. Contingencies have been shown to affect technology adoption decision making in the contexts of HIT [17, 70], manufacturing technologies [39], Internet adoption [66], IS development projects [77], and strategic alignment between technology adoption decisions and high-level strategy [72]. In general terms, a better organizational fit (or "congruence") with contingent variables is suggested to affect an organization's ability to innovate and, ultimately, the effectiveness of the organization. Interestingly, overall performance is not seen as maximization of individual variables (e.g., maximizing size) but, rather, as making decisions that result in optimal overall levels of multiple supply-side characteristics resulting in appropriate matches with contingent considerations [20].

We argue that ambulatory-care clinics are making strategic technology adoption decisions to find congruencies with an environment characterized by shifting demand, a rapid pace of technology change (especially as patient portals become more pervasive in health care), and coordination of care as cost pressures increase and quality outcomes come under increasing scrutiny. Specifically, we suggest that the strategic decision made by an ambulatory-care clinic to adopt a patient portal is made in the interests of maximizing organizational fit with such contingent factors. Following the framework by Weill and Olson [72], which suggests that congruence is a multistage process, our study focuses on early stage contingencies associated with adoption decisions. We consider the following contingencies: *demand contingencies* within the local market, including levels of education and income; *service contingencies* associated with the unique nature of how ambulatory-care clinics must coordinate care for patients trying to navigate a fragmented health-care delivery system; and *learning externality contingencies* associated with professional and social influences over health-care providers.

We posit that *demand contingencies* have not had a dominant influence in the IS literature because internal and enterprise IS are not often directly influenced by local consumer-oriented factors. It is interesting to note, though, that online services, such as online banking, are also examples of customer-facing portals, but research in this area has primarily focused on consumer *acceptance* (e.g., [64]) and correlated constructs such as *satisfaction* and *channel* preference (e.g., [18]). The same trend is seen in the marketing literature on self-service where constructs mostly focus on consumer *attitudes, acceptance,* and *satisfaction* (e.g., [41]). The very nature of this research that focuses on the demand-side suggests that demand factors are important considerations. Research has long shown that demand factors—such as higher levels of resources (e.g., more education, more income) as well as younger consumer segments with more venturesome personality traits—are often predictors of demand-side adoption [26]. For instance, the digital divide, often characterized by demographic characteristics such as income and age, has been shown to directly affect access to health information available on the Internet [11]. In addition, economic research has suggested that local clusters of business activity are likely to be influenced by demand factors (as well as by other firms and suppliers in the local area) [48]. Thus, supply-side adoption decisions are likely to be contingent on the specific local factors that define the market. Therefore, we suggest that local demand contingencies, such as consumers' levels of education and income, will influence supply-side decision making related to adoption of patient portals.

We consider *service contingencies* to be contingencies associated with the unique nature of the relationship between the ambulatory-care clinic and the patient. While many cases of self-service portals being offered to customers exist—such as instances of online banking portals and e-commerce portals—such self-service Web portals are primarily provided to consumers to increase convenience and reduce transaction costs associated with physical service encounters. Ambulatory-care clinics, however, are representative of a class of targeted, localized businesses that cater to a wider variety of customer (patient) needs, ranging from one-time, emergent needs to longer-term repeated coordination of care and relationship building. Relationships have been considered in the business-to-business context, especially in supply chain management, where strategic technology adoption can increase provider–supplier value and relationship quality through collaboration and information sharing. For instance, Iacovou et al. [34] found that electronic data interchange (EDI) adoption is more likely between partners who are dependent on each other. This finding suggests that an ongoing relationship where information exchange is needed can motivate adoption of technology designed to streamline the flow of information. In addition, the co-creation of value research stream suggests mutual benefits for firms that embrace the potential value of their consumers (e.g., [45]), and collaborative efforts are often at the core of health provider and patient relationships. However, to our knowledge, the nature of such lasting relationships between a firm and the firm's core customers has not been identified in other studies as a key predictor of supply-side adoption.

Learning externalities have traditionally been known to occur when information is shared between firms either through communication channels, through the movement of employees between firms, or through relationships with suppliers who supply multiple firms [61]. In the IT adoption context, learning externalities (also called "spillover effects") have been shown to affect demand-side adoption decisions, as in the case of the adoption of home computers when learning spillover effects were assessed at the city level [28] as well as supply-side adoption decisions as in the case of "social contagion" between medical providers seeking to adopt EMRs [1]. In addition, local clusters of business and business partners are known to influence one another through both competition and sharing of knowledge [48].

While controlling for select "dominant paradigm" characteristics (e.g., ambulatory-care clinic size, structure, management support, and competition), in the following section, we present specific arguments for our hypotheses related to the impact of *demand contingencies, service contingencies,* and *learning externality contingencies* on patient portal adoption by ambulatory-care clinics.

Hypothesis Development and Conceptual Research Model

Demand Contingencies

The delivery of health care in the United States is not uniform across all consumer segments. Characteristics of the patient population directly affect the way providers deliver health care, and the digital divide has been shown to affect health information access for disadvantaged populations [11]. More specifically, education, income, and age have been found to affect health information access via technology. It has also often been observed that consumer segments with more resources have better access to care [7] and those who are older often have a greater need for health-care services [37]. Those with more income, more education, and access to health insurance have been shown to have more opportunities to receive care, and disparities between those with and without such resources can result in fewer opportunities for preventive care and a lack of a single source of care [78]. Uninsured individuals are less likely to receive regular care from primary-care providers [43], more likely to have unmet health needs than their insured counterparts [7], and often suffer lower quality of life and poorer health outcomes [37]. It has also been reported that a majority (90.7 percent) of Americans over the age of 65 have at least one chronic condition and many (73.1 percent) had two or more chronic conditions, as of 2006 [37]. Moreover, urban environments with dense populations of health-care specialists may deliver care differently than rural providers [38].

There is marked trend in the industry toward patient-centered care, especially in urban settings [19], as it has been shown to improve outcomes in specific settings (e.g., [59]). Realigning the clinical support (including the underlying IS) to focus on patient needs is expected to improve the care process, the ability of patients to manage their conditions, and the coordination of care between episodes of clinical intervention [6].

To address patient-centric needs, many providers are beginning to implement patient portals with the capability for patients to become active participants in their own health care (e.g., [31]). In two recent case studies of patient portal usage by actual patients, individual differences were found to have significant effects on usage patterns. For instance, in the case of a patient portal targeted toward diabetes patients, lower levels of health literacy, less income, and older age were all negatively correlated with signing onto the portal [52]. In another case of a more general use patient portal, those who signed onto the patient portal the most were primarily younger, healthier, and more likely to have health insurance [74]. Thus, there can be marked differences in the demand for patient portals among economically advantaged and disadvantaged individuals. Finally, it has been shown that rural health-care providers often have slower HIT adoption rates than their urban counterparts [12], and this too may affect the demand for patient portals in areas where HIT is less prevalent.

Overall, these findings suggest that *demand contingencies* can have both positive and negative effects on care delivery and supply-side adoption of patient portals. Thus, ambulatory-care clinics are likely to seek congruence with the environment they operate in while also seeking to improve health outcomes by encouraging more active and responsible participation of their patients in their own health care.

> *Hypothesis 1 (Demand Contingencies): Demand characteristics will influence ambulatory-care clinic patient portal adoption decisions. (a) Ambulatory-care clinics in areas where patients have more college education or more income will be more likely to adopt patient portals. (b) Ambulatory-care clinics in areas where fewer patients have health insurance (uninsured) in areas where there is a higher proportion of the population aged 65 or older, or in rural areas will be less likely to adopt patient portals.*

Service Contingencies

Ambulatory-care clinics are heterogeneous with respect to the *type of service* they provide, and this difference in *service characteristics* may have a direct effect on patient portal adoption decisions. Specifically, we consider adoption decision differences between clinics that focus on longer-term relationships (i.e., primary care, specialties, and multispecialties) in contrast with clinics that focus on immediate needs (i.e., urgent care clinics). We posit that clinics with a primary focus on immediate needs (urgent care) will be less likely to adopt patient portals than primary care, specialty, and multispecialty ambulatory-care clinics where information dependence and patient–physician collaboration are essential elements of improved health outcomes.

In the medical context, *coordination of care* (and continuity of care) is a central focus of ambulatory clinic types that must operate in a fragmented delivery of care environment while trying to maximize positive health outcomes, per patient. This is especially true when dealing with patients with chronic conditions who must visit multiple providers [10]. A recent analysis of Medicare claims found a wide dispersion of care between multiple providers for patients and found that such dispersion increases with the number of chronic conditions [46]. Patients receiving coordinated continuity of care (as opposed to episodic delivery of care) from primary care, specialists, diagnostic centers, and other provider types are more likely to benefit from guideline-recommended care [2]. Coordinating care for patients can have a positive effect on the quality of care within the following contexts: surgery patients [27], use of primary care as a central point of coordination [50], and specialty care through referrals [23]. Primary care can be an effective hub for disease management for those with chronic conditions [50, 60]. Continuity of care therefore is a key consideration for physicians and patients alike in both primary care and specialty settings in a health system often characterized by episodic care delivery models [10].

Table 1 summarizes key differences between urgent care clinics, primary care clinics, specialty clinics, and multispecialty ambulatory-care clinics and demonstrates key considerations when comparing care associated with immediate needs versus long-term coordination and continuity.

In recent years, ambulatory-care providers have come under increasing pressure to improve patient health outcomes and reduce costs while dealing with changes in the health-care environment ranging from new policy to changes in insurance practices. Models of ambulatory care that embrace patient-centered care, advanced IS, and maintain and support ongoing relationships with patients have been touted in the literature as solutions to U.S. health-care system fragmentation (e.g., [40]). It has also been suggested that evidence-based medicine, sustained patient relationships with providers, and preventive care services can lead to better outcomes [57]. Finally, specialty practices "require a high degree of initiative to maintain accurate, information on patient being treated by multiple specialists" [62, p. 138]. Such specialty providers serving chronically ill populations with a large diversity of diagnoses are likely to deliver care differently than urgent care providers. Rather than treat symptoms through episodic delivery of care, chronic disease management models are emerging that require the evaluation of therapeutic adherence, adjustment, and outcome evaluation longitudinally for each affected patient. However, such models often require support from IS that assist with longitudinal tracking and analysis of data.

> *Hypothesis 2 (Service Contingencies): Ambulatory-care clinics offering services specializing in coordination of care and ongoing patient relationships (i.e., primary care, specialties, and multispecialties) will be more likely to adopt patient portals than those representing episodic delivery of care models (i.e., urgent care clinics).*

Learning Externality Contingencies

Health-care providers within the same geographic area often influence one another, especially with regard to HIT proliferation. Angst et al. [1] find that social proximity

Table 1. Ambulatory-Care Clinic Types and Characteristics

Ambulatory care clinic type	Characteristics
Urgent care clinic	Addresses immediate needs (where hospital admission or severe trauma needs are not required) Lower cost than hospital emergency departments Often encourages patients to seek routine and preventative care at local primary-care providers
Primary-care clinic	Often first point of contact in the health-care system Encourages preventative care Establishes relationships with patients and monitor health progress (not just immediate needs) Typically refer more complex cases to specialty clinics Becoming more of a central point of coordinated care for patients with one or more conditions Traditionally were self-employed physicians, but increasingly becoming part of group practices (multiple physicians) and part of integrated delivery systems (multiple providers owned by one corporation)
Specialty clinic	Specializes in the treatment of one specific condition or area of the body (e.g., neurology, cardiology) Physician requires specialized training in area of specialty Typically treats patients with chronic conditions Often requires careful patient medical record keeping and information tracking Beneficial for patients seeking very specific disease management, but fragmented delivery of care can lead to coordination problems or conflicting advice
Multispecialty clinic	Multiple health-care providers each offering specialty care within the same group of providers Provides for more coordination and continuity of care for patients who need to be referred to specialists Allows for easier sharing of patient records, information, and disease management

Sources: [37, 62].

between hospitals and the influence of hospitals considered at the forefront of technology adoption have significant effects on others' adoption of EMRs. Miller and Tucker [42] demonstrate that the quantity of EMR installations within the local area (health service area [HSA] in their context) has an impact on the "network benefits" within the HSA and the adoption self-perpetuates by leading to more local adoption of EMRs. Finally, Rye and Kimberly [51] suggest in their framework of HIT adoption that "connectedness" between providers and health organizations is likely to influence HIT adoption.

In addition, organizations such as the Health Information Management and Systems Society (HIMSS), the American Medical Association (AMA), and the Association of American Physicians (AAP) provide opportunities for members to obtain the most recent clinical practice and HIT information from centralized sources and other members. Such associations provide digital and printed content and typically have regular, local meetings for health-care providers to share information, network, and stay up-to-date on current trends. Such opportunities are especially valuable to providers considering HIT, as adoption is characterized by a number of known barriers (up-front financial costs, disruptions of workflows, learning curves, etc.) [22]. The "communities of practice" among local providers encourages active sharing of information and experiences with the goal of improving best practices for the membership as a whole [14]. In fact, it has been suggested that social interactions between physicians can have an impact on HIT adoption decisions [76] and that feedback loops within the local physician community can have effects on medical behaviors [44].

We seek to extend this understanding of *learning externality contingencies* to the context of customer-facing patient portals where ambulatory-care clinics are likely to influence each other, share information between providers, and trade best practices. We suggest that geographic areas with a higher percentage of clinics that have adopted patient portals are likely to have significant influence on adoption decisions made by other clinics in the same area.

Hypothesis 3 (Learning Externality Contingencies): Learning externalities associated with patient portals will have a positive effect on patient portal adoption by ambulatory-care clinics within the same geographic area.

"Dominant Paradigm" Controls

Many studies have confirmed the "dominant paradigm" of the adoption and diffusion of innovations within the context of HIT adoption. Multiple studies positively associate hospital or ambulatory-care clinic *size* (either number of beds or number of providers) with adoption (e.g., [1, 36]). Often, when hospitals or clinics are part of a health-care system (owned by a single entity)—which is a proxy for *structure, resources,* and *capabilities*—diffusion and adoption is positively affected (e.g., [1, 36]). *Competition* has also been shown to affect HIT adoption (e.g., [12, 36]). Finally, *management support,* in the form of the chief medical information officer (CMIO), may have a positive effect on HIT adoption within provider organizations [24]. In our model, we control for these "dominant" supply-side characteristics as well as the U.S. Census regions of the clinics (as was also done in [1, 16]). The conceptual model is depicted in Figure 1.

Data Sources

To examine the contingencies associated with patient portal adoption by U.S. ambulatory-care clinics, a cross-sectional data set was developed by merging data from the HIMSS Analytics Database 2010, the Area Resource File (ARF) 2009/2010, and the Bureau of Labor and Statistics (BLS) May 2009. The HIMSS data is an annual survey of nonfederal health-care facilities in the United States, including both acute

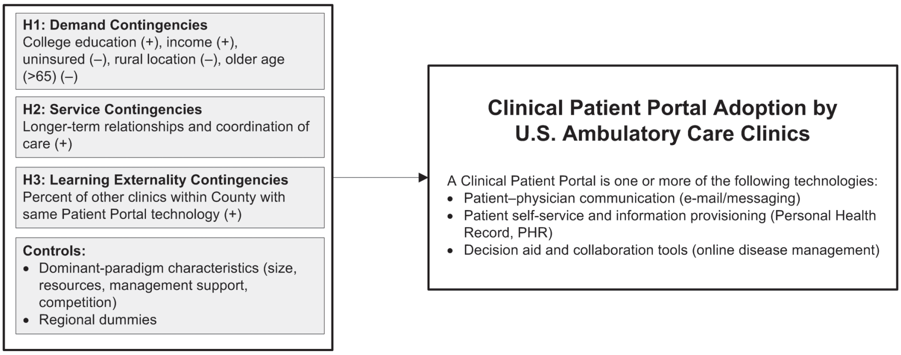

Figure 1. Conceptual Research Model

care hospitals and ambulatory-care providers. The ARF data contains U.S. county-level census and health data, including ambulatory-care data statistics for nearly all U.S. counties. The BLS data contains U.S. wage estimates for metropolitan and nonmetropolitan areas. When merged, the combined data (HIMSS, ARF, and BLS) contains detailed information for 21,375 ambulatory-care providers (9,165 of which have ambulatory EMR) as well as census, wage, and health data for nearly every U.S. county.

Method

Given that patient portal adoption by an ambulatory-care clinic typically requires an EMR to be implemented first,[2] we consider the adoption of patient portals to be subject to potential sample selection bias (based on whether the observed clinic has adopted EMR). Sample selection bias occurs when dependent variables are observed for a nonrandom portion of the sample that is dependent on another, potentially observable variable. In the original development of the sample selection correction model, wages of females were only observed for females that were in the workforce—an obvious bias when considering that many females chose not to participate in the workforce [30]. Such bias can be accounted for by using a two-stage model that includes a sample selection correction.

We adopt a nonlinear sample selection model that uses probit models at both stages (sample selection and full estimation stages) referred to as a *bivariate probit with sample selection.* We consider five binary dependent variables—adoption of any patient portal system (*PP_ANY*), adoption of disease management (*DMGT*: online, collaborative patient–clinician care for chronic conditions), patient-provider e-mail/messaging (*EMAIL*: online communication between patient and clinician), personal health records (*PHR*: online medical records, visit summaries, and diagnostic results shared with patients), or more than one of the three functions (*PP_MULT*). Our sample selection variable is also binary and equals one if the clinic has adopted ambulatory EMR. Correlation is assumed between the two error terms in the two equations, and maximum likelihood is applied for parameter estimation [67]. The model is as follows and is based on the discussion of sample selection models by Vella [68], the two-stage probit sample selection model used by Van de Ven and Van Praag [67], the discussion of sample selection models by Wooldridge [75], and the guidelines and formulas discussion in the Stata manual [58].[3]

The econometric model assumes a latent, underlying relationship that is not observed.

Latent equation:

$$y_j^* = x_j\beta + u_{1j}. \tag{1}$$

Such that a binary outcome is observed, for each observation j:

Probit equation:

$$y_j^{probit} = \left(y_j^* > 0\right). \tag{2}$$

But the dependent variable is observed only when (where z includes x and at least one exclusion restriction):

Selection equation:

$$y_j^{selection} = \left(z_j\gamma + u_{2j} > 0\right). \tag{3}$$

Therefore, the econometric model is similar to a two-stage least squares model. However, rather than assuming a linear relationship, it assumes nonlinearity in both stages, requires at least one exclusion restriction (similar to an econometric instrument) in the selection equation (the first-stage equation) that is not present in the second-stage equation and assumes that the second equation has a dependent variable that is only observed when the $y_j^{\text{selection}}$ dependent variable (from the first-stage sample selection equation) is greater than one.

Our empirical specification is an operationalization of this econometric model and explains EMR adoption by vectors of explanatory variables (Z) and controls (C) and explains adoption of patient portal systems by the same vectors (minus the exclusion restrictions); however, patient portal adoption is only observed when the EMR has also been adopted (EMR = 1).

First-stage probit selection equation:

$$\text{Prob}\left(EMR = 1 \middle| Z, C\right) = y_1 = \left(Z\gamma_1 + C\gamma_2 + u_1 > 0\right). \tag{4}$$

Second-stage probit equation:

$$\text{Prob}\left(PatientPortalSys = 1 \middle| EMR = 1, X, C\right) = Y_2 = \left(X\beta_1 + C\beta_2 + u_2 > 0\right), \tag{5}$$

where Y_2 is one of the patient portal binary dependent variables that represent adoption of a patient portal (*PP_ANY*), adoption of one of the specific patient portal functions (*DMGT*, *EMAIL*, *PHR*), or more than one of the three patient portal systems (*PP_MULT*); y_1 is a binary representation of EMR adoption and represents the basis for sample selection; X is a vector of exogenous explanatory variables; Z contains X

as well as the exogenous exclusion restrictions (explained in detail in the following paragraphs); *C* is a vector of control variables derived from diffusion of innovations theory and includes regional dummy variables; u_1 is the random error term in the first stage; and u_2 is the random error term in the second stage. This model assumes that the error terms are independent and have a bivariate normal distribution, but also that the errors are correlated [75, p. 570]. The correlation between the error terms is the reason for using sample selection correction, and the correlation between u_1 and u_2 is represented by ρ.

Exclusion Restriction

For a two-stage binary sample selection model to be estimated without bias, at least one variable is needed in the first-stage model that is not present in the second-stage model (exclusion restriction) [75, p. 569]. However, if the exclusion restrictions are endogenous (correlated with both error terms), the model coefficients are subject to bias. Since the dependent variables are all IT related, any variable that is also IT related is also likely to be endogenous (even if the IT performs a different function). Therefore, we now consider ways in which EMR and patient portals are different and approach exclusion restriction selection by examining these differences.

We consider that EMRs are implemented by ambulatory-care clinics to replace paper records and inefficient processes. EMRs are often adopted in the hopes of improving business process efficiency and productivity, but we acknowledge that such efficiencies are not always realized (e.g., [47]). Therefore, EMR adoption can be considered to be an IS designed with business process efficiency and improvement in mind, even if efficiencies do not always live up to expectations. In contrast, the clinical patient portals considered in this paper are associated with patient relationship management, information provisioning, and health outcome collaboration. While EMR adoption can be moderated by operational costs to the clinical practices when EMR is implemented, these operational cost considerations would be less relevant to patient portal adoption by ambulatory-care clinics. Therefore, we consider the local wages of the jobs that might be replaced (or reduced) by EMR to be highly correlated with EMR, but not with patient portals, as good candidates for variables to be used as exclusion restrictions. The exclusion restrictions are valid as long as they are correlated with portal adoption only through the *EMR* variable.

It is suggested that EMR reduces the cost of medical transcription of patient records and staffing in regard to management of paper records [32, 71]. Therefore, we obtained the wages of *medical transcriptionists* and *medical records and health information technicians* for the BLS area of each ambulatory-care clinic within our sample. Because absolute wages reflect labor expense and cost of living and high wages are distinct from high prices in general (i.e., overhead such as rent), we adjust the wages by average wages for the entire BLS area (for “All Occupations”). The unadjusted wages include cost-of-living, which is endogenous, so we normalize to isolate the wage effect. Therefore, our exclusion restrictions are defined as adjusted medical transcriptionist wage (*ADJMTWAGE*) and adjusted medical records wage (*ADJMRWAGE*) and are defined as follows (for each BLS area):

$$ADJMTWAGE_{BLSArea} = \frac{MedTransWage_{BLSArea}}{AllOccupationsWage_{BLSArea}} \tag{6}$$

$$ADJMRWAGE_{BLSArea} = \frac{MedRecordsWage_{BLSArea}}{AllOccupationsWage_{BLSArea}}. \tag{7}$$

Finally, one potential issue is that the variables representing *demand contingencies* come from the ARF data, which is aggregated by county. However, our full data set contains data at the ambulatory clinic level. This means that the ARF data are repeated for every observation of an ambulatory-care clinic within the same county. Therefore, it is possible that our results will be biased because of the nonindependent nature of the grouped data as it is represented in our data set. To correct for this issue, we take a conservative approach and cluster the standard errors by U.S. county.

Variables

The variables (and descriptive statistics) are described in more detail in Table 2. Approximately 43 percent of ambulatory-care providers have adopted ambulatory EMR within this data set, and approximately 22 percent of ambulatory-care providers that have ambulatory EMR have also adopted at least one patient portal system. The first two sections of the table (*selection dependent variable* and *dependent variables*) describe the dependent variables used in the two-stage sample selection correction model. The second stage of adoption, adopting a patient portal, is operationalized through the presence of at least one of patient-centric functions of a patient portal.

The remaining sections describe the independent variables. *Demand contingencies* (H1) are operationalized as characteristics of the consumers within each U.S. county (from the ARF data). *Service contingencies* (H2) are binary variables representing four types of ambulatory-care clinics where the reference category (urgent care clinics) represents transaction-based (episodic delivery of care) services. The remaining three binary variables represent ambulatory-care clinic types that are typically associated with coordination of care and ongoing patient–provider relationships (primary care, specialty clinics, and multispecialty clinics). *Learning externality contingencies* (H3) are operationalized as the percentage of adopters of the same practice type who have adopted a related patient portal system within the same county (similar proxies were used by Ayers et al. [3] and Miller and Tucker [42]).

To control for diffusion of innovation (DOI) "dominant paradigm" characteristics, we have included proxies for size (log of the number of physicians), resources and capabilities (member of an integrated delivery system that provides care under a larger, corporate umbrella), management support (the presence of a CMIO), and the number of competitors (of the same practice type) within the same zip code (based on Garnick et al. [25]). The *region dummies* are from the U.S. Census Bureau definition of regions and control for regional differences (used similarly in Angst et al. [1] and DesRoches et al. [16]). And, finally, the *exclusion restrictions* are variables correlated with EMR, but not directly with patient portal systems, and are used to remove (or reduce) bias in the two-stage model.

As indicated in Table 2, each of the three data sets aggregates data at a different level. HIMSS provides comprehensive *firm-level* data for a significant majority of ambulatory-care clinics within the United States; the ARF provides *county-level* data (by Federal Information Processing Standard [FIPS] state and country codes); and the BLS data is organized by metropolitan service area (MSA), nonmetropolitan service area (Non-MSA), metropolitan division (MDiv), and New England city and town areas (NECTA). HIMSS and ARF were merged with corresponding FIPS codes and all but five observations matched directly. For those five "nonmatched" observations, ARF data averaged for the state was used. BLS data was merged with the HIMSS and ARF data by matching MSAs, Non-MSAs, MDivs, and NECTAs with the corresponding FIPS codes. About 16 percent of the observations could not be matched directly with BLS data and, in those cases, BLS state-level data for the same time period, May 2009 (also available from the BLS) was applied.

Results

Table 3 summarizes the results from the empirical analysis. The significance of the Wald-statistic (test of independent questions) in all two-stage models (bivariate probit models) suggests that the unrestricted model (the model with the exclusion restrictions included) is favored over the restricted model. In addition, the two exclusion restrictions (*ADJMTWAGE* and *ADJMRWAGE*) have significant and positive coefficients in the first-stage (selection) equation where adoption of ambulatory EMR (*EMR*) is the dependent variable. Because data is missing for some variables (e.g., number of physicians was not available for all the practices and some wage data was unavailable for some counties), 19,702 observations are used in the models (7.8 percent missing data). Of the 19,702 observations, 11,225 are censored (i.e., do not have ambulatory EMR); 8,477 are uncensored (i.e., have ambulatory EMR and no missing data). Correlations between variables are within acceptable ranges. Pseudo-R^2 values range from 38.9 percent (*PP_ANY*) to 48.1 percent (*DMGT* and *PP_MULT*).

Demand Contingencies

While higher per capita *income* was not found to be associated with a higher propensity to adopt any of the patient portal systems, we do observe some positive effects of the percent of *college educated* individuals within a county on patient portal adoption. We observe that a higher percentage of *college educated* individuals within a county is negatively associated with EMR adoption, yet positively associated with a higher propensity to adopt *disease management* (*DMGT*), *personal health records* (*PHR*), and *multiple systems* (*PP_MULT*). Therefore, these results provide weak partial

Table 2. Descriptive Statistics for Empirical Model Data

	Variable	Description	Obs.	Mean	SD	Min	Max
Sample selection dependent variable	EMR	1 = has ambulatory EMR	21,375	0.429	0.495	0	1
Dependent variables	PP_ANY	1 = has at least one of the three patient portal systems: DMGT, EMAIL, or PHR	9,165	0.225	0.418	0	1
	DMGT	1 = has online disease management	9,165	0.125	0.331	0	1
	EMAIL	1 = has patient-provider e-mail or messaging	9,165	0.209	0.407	0	1
	PHR	1 = has personal health record (PHR)	9,165	0.111	0.314	0	1
	PP_MULT	1 = has adopted 2 or 3 patient portal systems (DMGT, EMAIL, or PHR)	9,165	0.148	0.355	0	1
Demand contingencies	Percent college educated	Percent of population within U.S. county with college education	21,374	23.896	9.449	0	63.700
	Income (log)	Log of per capita income within U.S. county	21,374	10.440	0.843	0	11.796
	Rural location	1 = rural location	21,375	0.162	0.368	0	1
	Percent uninsured	Percent of population within U.S. county uninsured	21,374	12.913	4.109	0	37.900
	Percent of population > 65 years of age	Percent of population within U.S. county over 65	21,375	13.465	3.505	0	36.188

(continues)

Table 2. Continued

	Variable	Description	Obs.	Mean	SD	Min	Max
Service contingencies	Urgent care clinic*	1 = urgent care/emergency clinic	21,375	0.035	0.183	0	1
	Primary-care clinic	1 = family practice, internal medicine, pediatrics, OB/Gyn, or primary care	21,375	0.447	0.497	0	1
	Specialty clinic	1 = medical specialty practice or diagnostics provider	21,375	0.430	0.494	0	1
	Multispecialty clinic	1 = multispecialty practice	21,375	0.091	0.287	0	1
Learning externality contingencies	PPAny externalities	Percent of same practice types (in same county) with any at least one of the three (DMGT, EMAIL, or PHR) patient portal systems	21,375	8.306	17.769	0	94.444
	Disease management externalities	Percent of same practice types (in same county) with disease management implemented	21,375	4.541	13.738	0	94.444
	E-mail externalities	Percent of same practice types (in same county) with patient-provider e-mail or messaging	21,375	7.755	17.407	0	94.444
	PHR externalities	Percent of same practice types (in same county) with PHR	21,375	4.011	12.900	0	91.667
	PPMult externalities	Percent of same practice types (in same county) with multiple (2 or 3) patient portal systems (DMGT, EMAIL, or PHR)	21,375	5.436	15.212	0	94.444

	EMR externalities	Percent of same practice types (in same county) with ambulatory EMR	21,375	35.092	30.704	0	97.674
DOI controls	Integrated delivery system	1 = practice is a member of an integrated delivery system	21,375	0.635	0.481	0	1
	Number of physicians (log)	Log of number of physicians	20,694	1.207	0.995	0	6.686
	CMIO present	1 = parent hospital has chief medical information officer	21,375	0.276	0.447	0	1
	Competition (within zip code)	Number of same ambulatory practice types in the same zip code	21,375	0.659	1.363	0	19.000
Regional dummies	Northeast region*	1 = located in northeast U.S. region	21,375	0.219	0.413	0	1
	Midwest region	1 = located in midwest U.S. region	21,375	0.337	0.473	0	1
	Southern region	1 = located in southern U.S. region	21,375	0.294	0.456	0	1
	Western region	1 = located in western U.S. region	21,375	0.151	0.358	0	1
Exclusion restrictions	Adjusted medical transcriptionist wage (ADJMTWAGE)	Medical transcriptionist wage in BLS area adjusted by average wages across all occupations in the BLS area	20,365	0.817	0.091	0.518	1.489
	Adjusted medical records and health information technician wage (ADJMRWAGE)	Medical records and health information technician wage in BLS area adjusted by average wages across all occupations in the BLS area	20,365	0.823	0.087	0.574	1.259

Notes: Obs. = number of observations; SD = standard deviation; Min = minimum; Max = maximum. * Reference category.

Table 3. Patient Portal Adoption Two-Stage Model Results

	EMR Probit (selection equation)	PP_ANY Bivariate probit	DMGT Bivariate probit	EMAIL Bivariate probit	PHR Bivariate probit	PP_MULT Bivariate probit
Demand contingencies (H1)						
Percent college educated	–0.008***	0.000	0.007***	0.000	0.008***	0.008***
	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Income (log)	0.007	0.047	–0.003	0.04	–0.001	0
	(0.013)	(0.040)	(0.016)	(0.040)	(0.022)	(0.028)
Rural location	0.210***	0.320***	–0.109	0.297**	–0.131*	–0.035
	(0.046)	(0.087)	(0.061)	(0.092)	(0.052)	(0.073)
Percent uninsured	–0.024***	–0.015*	0.013**	–0.015	0.014**	0.012**
	(0.004)	(0.008)	(0.004)	(0.009)	(0.004)	(0.005)
Percent of population > 65 years of age	–0.007	–0.015	–0.007	–0.012	0.005	–0.001
	(0.004)	(0.008)	(0.006)	(0.008)	(0.005)	(0.005)
Service contingencies (H2)[a]						
Primary care clinic	–0.417***	–0.055	0.471***	–0.019	0.386***	0.411***
	(0.051)	(0.085)	(0.069)	(0.097)	(0.057)	(0.062)
Specialty clinic	–0.450***	–0.045	0.549***	–0.019	0.453***	0.458***
	(0.054)	(0.088)	(0.074)	(0.100)	(0.059)	(0.064)
Multispecialty clinic	–0.162**	–0.045	0.296***	–0.014	0.200**	0.229**
	(0.061)	(0.092)	(0.079)	(0.099)	(0.066)	(0.071)

Learning externality contingencies (H3)						
PPAny externalities		0.042***				
		(0.002)				
Disease management externalities			0.036***			
			(0.002)			
E-mail externalities				0.043***		
				(0.003)		
PHR externalities					0.035***	
					(0.002)	
PPMult externalities						0.036***
						(0.002)
EMR externalities	0.025***	–0.004*	–0.027***	–0.005	–0.026***	–0.027***
	(0.000)	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)
DOI "dominant paradigm" controls						
Integrated delivery system	0.028	0.190	0.144	0.286**	0.221**	0.254*
	(0.047)	(0.100)	(0.094)	(0.105)	(0.072)	(0.118)
Number of physicians (log)	0.153***	0.117***	–0.076**	0.132***	–0.080***	–0.058
	(0.014)	(0.027)	(0.028)	(0.029)	(0.023)	(0.030)
CMIO present	0.168**	–0.035	–0.172*	0.014	–0.201***	–0.145*
	(0.053)	(0.087)	(0.069)	(0.091)	(0.050)	(0.064)
Competition (within zip code)	–0.005	–0.011	–0.003	–0.010	–0.015*	–0.003
	(0.008)	(0.007)	(0.005)	(0.007)	(0.008)	(0.006)

(continues)

Table 3. Continued

	EMR Probit (selection equation)	PP_ANY Bivariate probit	DMGT Bivariate probit	EMAIL Bivariate probit	PHR Bivariate probit	PP_MULT Bivariate probit
Region dummies[b]						
Midwest region	0.046	0.225*	–0.052	0.262**	–0.059	–0.021
	(0.031)	(0.089)	(0.042)	(0.089)	(0.041)	(0.047)
Southern region	0.124***	0.090	–0.144**	0.100	–0.090*	–0.098
	(0.036)	(0.100)	(0.054)	(0.101)	(0.046)	(0.052)
Western region	0.202***	0.216*	–0.142**	0.259*	–0.225***	–0.136*
	(0.044)	(0.103)	(0.050)	(0.106)	(0.051)	(0.055)
Exclusion restrictions						
ADJMTWAGE	0.355**					
	(0.128)					
ADJMRWAGE	0.417**					
	(0.149)					
Pseudo R^2	0.2495	0.389	0.481	0.403	0.459	0.481
Rho (ρ)		0.713	–0.980	0.650	–0.990	–0.970
Wald-statistic *p*-value		0.003	0.000	0.045	0.000	0.000

Notes: Robust standard errors clustered by county are in parentheses. [a] Urgent care (*t_urg*) omitted. [b] Northeast region (*rgnne*) omitted. *** Significant at $p < 0.001$, ** significant at $p < 0.01$, * significant at $p < 0.05$.

support for H1a, suggesting that *college education* and *income* would be positively associated with supply-side patient portal adoption. Discussion of why more education may negatively affect EMR adoption yet positively affect patient portal adoption is discussed later.

The effects for H1b, suggesting that *rural* locations, a higher percentage of *uninsured* individuals within a county, and a higher proportion of individuals *over the age of 65* would be negatively associated with patient portal adoptions are mixed. A *rural* location positively affects EMR adoption as well as adoption of at least one patient portal system (*PP_ANY*) and patient-provider e-mail or online messaging (*EMAIL*). However, a *rural* location is negatively associated with online disease management (*DMGT*) and *PHR* systems. Interestingly, though, a higher percentage of *uninsured* individuals within a county has a positive effect on the propensity to adopt *DMGT*, *PHR*, and multiple systems (*PP_MULT*), but has a negative effect in the selection equation (*EMR*) as well as a negative affect on *EMAIL* and *PP_ANY*, which is contrary to our hypothesis. In addition, a higher percentage of the population *over 65* is insignificant in all the models.

In a follow-up analysis suggested by an anonymous reviewer, we also assessed the impact of the percentage of *unemployed* individuals within a county on supply-side patient portal adoption. We found that *unemployment* was insignificant in all the models except for the model where *PHR* was the dependent variable. The inclusion of *unemployment* as a proxy for those who are economically disadvantaged in the *PHR* model resulted a negative and marginally significant result ($\beta = -0.020$, $p = 0.058$).

Service Contingencies

While all three types of ambulatory-care clinics—primary care, specialty clinics, and multispecialty clinics—are *less* likely to adopt ambulatory EMR than urgent care clinics (the reference category), they are *more* likely to adopt online disease management (*DMGT*), *PHR*, and multiple systems (*PP_MULT*). Significant and relatively high magnitude positive effects are observed in all these cases. In addition, these results are consistent for each clinic type. Primary care clinics are more likely to have disease management (*DMGT*), *PHR,* and multiple systems (*PP_MULT*). The same is true for specialty and multispecialty clinics. These significant effects provide strong support for H2 (Service Contingencies) in regard to the propensity to adopt patient portals for care delivery models focused on coordination of care and ongoing patient relationships as opposed to episodic delivery of care.

While not reported directly in the final results, we also tested for the effects of the *age of the ambulatory-care clinic* on patient portal adoption. The number of years the clinic has been in business was used as a proxy for a more established and reliable client base. Such a client base may be more interested in online management of records, information, and services because of a longer-term relationship with the provider that could include an archive of historical information between the patient and provider established over an extended time period. However, there may be challenges with digitizing historical data and, therefore, may also negatively affect patient portal adoption. The *practice age* variable was not used in the final models because the year of inception of the practice was only available for about two-thirds of the sample (or 14,397 observations out of 21,375 total observations). However, subsequent analyses using the same models as above and including the *practice age* variable, even though this resulted in a censored sample, suggest that increased age of practices slightly increases the adoption propensity of EMR ($\beta = 0.011$, $p = 0.000$) and slightly decreases patient-provider e-mail adoption propensity ($\beta = -0.009$, $p = 0.000$), but does not have significant effects on any of the other dependent variables (*PP_ANY*, *DMGT*, *PHR*, *PP_MULT*). This could be an area for future research.

Learning Externality Contingencies

The highly significant (and positive) effects of the adoption by other like clinics within the same county of the same patient portal system suggest strong support for learning externality contingencies. The adoption of at least one patient portal system by the same clinic type (*PPAny Externalities*) had a positive and significant effect on the propensity to adopt at least one system (*PP_ANY*). All the other variables associated with externalities were found to have positive and significant effects on patient portal adoption, within their respective models. These findings provide strong support for H3 (Learning Externalities).

In a follow-up analysis, we also explored the effects of interactions between *demand contingencies* and *learning externality contingencies* on adoption propensity.[4] Each continuous *demand contingency* variable (*percent college educated*, *income*, *uninsured*, and *population over 65*) was interacted with each *learning externality contingency* variable. The results suggested that higher levels of *college education* and an increased population of *individuals over 65* marginally increased adoption propensity in areas where higher levels of *learning externalities* are present. Specifically, when the interactions were included in the *PP_ANY* model, which is the dependent variable for the adoption of at least one patient portal system, the following low magnitude, but significant interactions coefficients were observed: *PPAny Externalities * Percent College Educated* ($\beta = 0.0003$, $p = 0.029$) and *PPAny Externalities * Percent of Population > 65 Years of Age* ($\beta = 0.0013$, $p = 0.003$). Similar results were observed for the disease management (*DMGT*) and patient-provider e-mail (*EMAIL*) dependent variables. Such interactions could be an area for further research.

Control Variables

The "dominant paradigm" controls exhibited mixed results. Adoption of EMR is more likely for larger practices (*number of physicians*) and those that are associated with a chief medical information officer (*CMIO*), but does not appear to be affected by *competition within the same zip code* or by membership in an *integrated delivery system* (*IDS*). Membership in an *IDS* did affect the propensity to adopt at least one patient portal system (*PP_ANY*), multiple systems (*PP_MULT*), *EMAIL*, and *PHR*.

However, the size of the practice (*number of physicians*) negatively affected *DMGT*, *PHR*, and *PP_MULT*, but positively affected *PP_ANY* and *EMAIL*. The presence of a *CMIO* negatively affected *DMGT*, *PHR*, and *PP_MULT*. Finally, some regional effects were observed (e.g., some regions are more likely to adopt than others), and the significance of these regional factors suggests that inclusion of these dummies helps to reduce potential regional biases.

Summary of the Results

Our findings are summarized in Table 4. The strongest support is observed for H2 (Service Contingencies) and H3 (Learning Externality Contingencies).

Discussion and Implications

THIS PAPER SOUGHT TO DEMONSTRATE that the supply-side adoption of patient portals by ambulatory-care clinics is affected by contingent factors. Specifically, using diffusion of innovations literature and contingency theory as the theoretical base, we expanded upon the firm characteristics traditionally considered to be predictors of innovative, supply-side adoption (firm size, slack resources, competition, capabilities, management support, etc.) and examined how *demand contingencies, service contingencies,* and *learning externality contingencies* affect the propensity for patient portal adoption by ambulatory-care clinics within the United States. In addition, we employed a two-stage empirical model that controlled for sample selection, given that EMRs are often adopted prior to patient portals.

Our primary finding is that "dominant" firm traits are important indicators of patient portal adoption by ambulatory-care clinics but do not tell the entire story. Contingencies, particularly in regard to *service contingencies* related to ongoing patient relationships and coordination of care as well as *learning externalities* within the same geographical area have significant effects on the propensity to adopt. To a lesser extent, we also observe some effects from local *demand contingencies* that may play a small but significant role in adoption decisions.

Some of our findings are supported by other studies that have demonstrated that relationships between firms and consumers are key business considerations [53], externalities are an essential consideration in HIT adoption [3, 42], and demand characteristics are key indicators of innovation diffusion [26], especially in the context of the digital divide [11]. Our study contributes to theory and practice by combining these considerations within the context of patient portal adoption and extends previous findings by demonstrating that such technology adoption is about the *link* between the supply-side and demand-side (and social interactions between providers), not just "dominant" firm characteristics [21] or technology "acceptance" considerations (e.g., [69]). In addition, we use a two-stage model of adoption, which controls for sample selection associated with ambulatory EMR adoption. Current models in this context often employ structural equation models (e.g., [13]). We demonstrate that

Table 4. Summary of Results

Hypothesis	Results
H1a (Demand contingencies): college education (+) and income (+)	College education weakly supported; income not supported
H1b (Demand contingencies): uninsured (–), rural (–), and over 65 years of age (–)	Rural findings mixed; uninsured findings mixed; over 65 not supported
H2 (Service contingencies)	Strongly supported (for disease management, PHR, and multiple systems)
H3 (Learning externality contingencies)	Strongly supported (for all patient portal systems)
Control variables: Dominant paradigm characteristics	Mixed findings (effects are different for EMR versus patient portal adoption)
Control variables: Regional dummies	Some regional effects are present

the *bivariate probit with selection model* is appropriate (and even necessary) for this context and suggest that future models of adoption in the context of customer-facing systems may need to control for the presence of preexisting IS (e.g., EMRs) to reduce coefficient bias.

Demand Contingencies

We find that areas with a higher percentage of college-educated individuals are more likely to have patient portal adoptions by ambulatory-care clinics and do not find support for the impact of income on patient portal adoptions. These findings are somewhat consistent with previous research suggesting that populations with more resources are more likely to have better access to health care (e.g., [7]). However, with regard to income, it has been suggested that more of an emphasis on primary care can offset the disparity of health-care delivery associated with lower income, and we may be observing such an effect in these results [54].

Interestingly, we find that a higher percentage of college-educated individuals and individuals over the age of 65 has a negative impact on EMR adoption, yet college education has a positive impact on patient portal adoption and age only has a marginally significant negative effect in one model. Why the change in signs? It is possible that ambulatory-care providers are comfortable with paper records, especially when dealing with an established base of patients with long histories. The many challenges of moving from paper to electronic records have been well documented, and incentives are needed to overcome such hurdles [4]. In addition, our inclusion of the variable *practice age* in a follow-up analysis resulted in insignificant effects on patient portal adoption. Therefore, we believe these results provide support for recent policies that provide financial incentives to health-care providers to adopt HIT. Specifically, the Health Information Technology for Economic and Clinical Health (HITECH) provisions of the American Recovery and Reinvestment Act (ARRA) of 2009 are incentivizing and removing significant barriers to HIT adoption. As such barriers to the first stage of technology investment (EMR, in this case) are removed or reduced, the valuable second-order effects of extending patient portals to consumers are more likely to materialize. Our findings suggest that overcoming the hurdle of EMR adoption is challenging, which is why the relationship between some demographic characteristics and provider types are negative for EMR adoption, but once the hurdle is overcome, adoption of a patient portal is much easier. We believe that these findings could motivate future research in the area of increasing returns to scope when barriers in the first stage(s) of adoption are reduced and potential improvements to health outcomes related to reaching out to patients through a follow-on investment (the patient portal).

We also note that a higher percentage of uninsured within a county is positively associated with some forms of patient portal adoption (contrary to our hypothesis), while negatively associated with other forms, and that rural location also exhibit somewhat mixed results. While unanticipated, these findings seem to reinforce some recent empirical research in this area. A recent study found that adoption of ambulatory EMR by physician practices is not significantly affected by urban versus rural location and also did not find a significant effect of the presence of more uninsured on such HIT adoption decisions [16]. In addition, lack of insurance does not always result in being turned away from nonemergency care clinics, and other options, such as prepayment, are also available [73]. Finally, we find that rural locations are more likely to adopt patient-provider e-mail/messaging, and this could suggest that rural providers are seeking to increase convenience and provide alternative communication channels to patients in areas with limited provider availability. However, some of the more advanced technologies, including online disease management and PHRs, are less likely to be adopted by rural providers, and this is consistent with prior research finding that rural providers often have slower HIT adoption rates (e.g., [12]).

Service Contingencies

We find strong support for increased propensity of adoption among ambulatory-care services specializing in primary care, specialty care, and multispecialty care when compared to the propensity of adoption among urgent care clinics, particularly for online disease management, PHRs, and adoption of multiple systems. These findings suggest that information dependence and collaboration capabilities are key considerations when service delivery is focused on longer-term needs and establishment of relationships versus one-time transactions (i.e., immediate needs addressed by urgent care). This appears to be especially true for those who may have chronic conditions as online disease management and PHRs are targeted toward those with information-intensive conditions, such as diabetes (e.g., [55]). Just as IS established for information sharing and processing are beneficial to both buyers and suppliers in supply chain relationships and for reducing uncertainty in cooperative partnerships between organizations, so too can information sharing and collaborative health management tools be beneficial for the patient–physician relationship.

Learning Externality Contingencies

Our findings related to *learning externality contingencies* show that "social contagion" [1] is often present in consumer-facing HIT adoption decisions and that adopters within the same geographic area often have influence over other potential adopters in the same area [42]. Positive learning externalities may encourage adoption through information sharing and best practices emerging among physicians who share between themselves [1, 3]. These findings provide support for developing initiatives targeted toward motivating adoption through peer influences.

Conclusion

This study has demonstrated that patient portal adoption is dependent on prior technology adoption and is influenced not only by the "dominant paradigm" of the diffusion of innovations [21] but also *service contingencies* associated with longer-term relationships and coordination of care, *learning externalities contingencies,* and to a lesser extent, select *demand contingencies.*

The findings are particularly relevant from the perspective of real-options literature (e.g., [5]) that suggests that return on investments are often gained with secondary investment decisions that build upon initial investments. Ambulatory-care clinics that have adopted patient portals have exercised an option resulting from an initial and likely costly, investment into an EMR. The patient portal is a follow-on option that represents risks (e.g., Will patients actually use patient portals?) as well as many potential rewards (e.g., rural patients will have a more effective communication medium and chronic diseases are easier to manage). Therefore, there are uncertain returns based on demand factors and even externality effects. If other ambulatory-care clinics in the same market area adopt patient portals, then consumers may find more benefit from adoption given the potential to electronically transmit and share records and information between providers. However, the unknowns associated with adoption by neighboring providers and the diversity of demand creates an environment where patient portal adoption is potentially risky. Therefore, future research into whether and how EMR adoption may realize better returns on investment through follow-on investments (e.g., patient portal adoption) would be an interesting extension of this work.

The findings also provide support for examining multiple levels of innovation sophistication in patient portal adoption. Clinical patient portals are not just one system, but often a combination of systems, including disease management, e-mail/messaging, and personal health records. Our models accounted for adoption of a single system or multiple systems. Therefore, we suggest that future models consider consumer technology adoption as a choice of innovation sophistication among a range of options that may aid various consumer segments in distinct ways.

We acknowledge that our study is limited by a single context (U.S. health care) and self-reported data. However, we believe that the model developed in this research could be extended to other industries where there is an increasing emphasis on information and relationship dependence between the firm and the consumer. We also acknowledge that our model is limited by our selection of exclusion restrictions (wage variables) that we suggest are exogenous. Overall, we have demonstrated that dominant firm traits tell only part of the story and, as firms directly engage and rely on consumer input and collaboration, firms will need to strategically consider how consumer demand, relationship expectations, and the need to learn from others who have already adopted will affect the technology adoption decision-making process.

Notes

1. Obtained from the Health Information Management and Systems Society (HIMSS) Health Information Infrastructure survey for 2010.

2. EMRs are not necessarily a prerequisite for patient-provider e-mail, but only 111 (or 0.52 percent) of ambulatory-care providers in our data set had adopted patient-provider e-mail or messaging and *did not* have an EMR.

3. We utilized the "heckprob" command in Stata for estimation (see [58, pp. 9–11]).

4. *Service contingencies* were binary variables and, therefore, not included in the analysis of interactions.

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