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The impact of health information technology on hospital productivity

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Health information technology (IT) has been championed as a tool that can transform health care delivery. We estimate the parameters of a value-added hospital production function correcting for endogenous input choices to assess the private returns hospitals earn from health IT. Despite high marginal products, the total benefits from expanded IT adoption are modest. Over the span of our data, health IT inputs increased by more than 210% and contributed about 6% to the increase in value-added. Not-for-profits invested more heavily and differently in IT. Finally, we find no compelling evidence of labor complementarities or network externalities from competitors' IT investment.

1. Introduction

■ By most accounts, the US health care sector is inefficient. Health policy commentators have long advocated increased health information technology (IT) adoption as a means of increasing health care quality while constraining costs (Hillestad et al., 2005). The Institute of Medicine, for example, has advocated increased health IT investments (Institute of Medicine, 1999, 2001, 2003). Similarly, health policy analysts have noted that other OECD countries utilize more health IT than the US, and this may be an important reason that health care costs are lower in the OECD. The implication is that if the US deepened its use of health IT, it will move the US toward the productive frontier for health care delivery.

In response to this call, the federal government has made increasing IT investments by private health care providers a priority. In 2004, President George Bush established the Office of the National Coordinator (ONC) for Health Information Technology, which is tasked with the

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development and implementation of a strategic plan to guide the nationwide implementation of health IT. In 2009, as part of the American Recovery and Reinvestment Act, President Barack Obama signed the Health Information Technology for Economic and Clinical Health (HITECH) Act which allocates an estimated $27 billion in incentive payments for hospitals and health professionals to adopt and effectively use certified electronic health records (ARRA, 2009).[1] Furthermore, hospitals that fail to achieve the "meaningful use" of health IT by 2015 will face reductions in Medicare payments.

The significant role the federal government plays in promoting the adoption and diffusion of health IT suggests a divergence between private incentives and social benefits from adopting these technologies. Despite the widespread belief that health IT can address many of the health care system ailments and many studies in the medical and health services research literature, there is little consensus regarding the impact of health IT on provider costs and revenues or the quality of care patients receive.[2] This literature also points to the difficult IT investment decisions hospitals face because of the significant costs associated with large-scale health IT implementation and *a priori* uncertainty over the returns hospitals can expect from implementing health IT. In other contexts, IT adoption has been shown to improve health outcomes (Athey and Stern, 2002). We provide evidence on the impact of IT investments on hospital productivity to assess the private benefits from hospitals' adoption of health IT.

Even if hospital IT significantly increases the quality of patient care, hospitals will not capture these social gains unless they can translate clinical improvements into higher profits through increased prices, lower operating costs, or higher patient volumes. Hospitals face several challenges in transforming quality improvements into profits. Evidence from the introduction of hospital report cards suggest that patient preferences are weakly related to measurable quality and, therefore, hospital patient volumes are not likely to be affected by health IT utilization (Culter, Huckman, and Landrum, 2004). Typically, half of hospital revenues are from publicly insured patients where hospitals are reimbursed according to a fixed, administered fee schedule. These fee schedules limit hospitals' ability to charge higher prices for improved quality of care. Quality improvements may, however, reduce lengths of stay which, in turn, could reduce costs. Hospitals' inability to profit from IT-driven quality improvements may lead to inefficiently low IT investments.[3]

Hospitals' IT investments may affect productivity through a variety of mechanisms. Hospitals may benefit from similar information systems employed in other service industries. Applications such as supply chain management, accounting, and billing would, for example, reduce transaction costs and improve resource allocation. Most, if not all, of the returns from these applications should be internalized by hospitals.[4] The consequences of clinical systems, such as electronic medical records (EMRs), are more complicated. Although these systems may improve resource allocation

[1] The cause of increasing health IT spending has been advocated at the highest levels of the federal government. In a January 3, 2009 radio address, President Obama stated, "We will update and computerize our health care system to cut red tape, prevent medical mistakes, and help reduce health care costs by billions of dollars each year."

[2] See Buntin et al. (2011), Lapointe, Mignerate, and Vedel (2011), Black et al. (2011) for reviews of the relevant clinical and informatics literature. More recent econometric studies have also found mixed results regarding the quality impact of health IT adoption. Tucker and Miller (2011) find that the adoption of electronic medical records (EMRs) provide meaningful clinical benefits to newborns, and McCullough, Parente, and Town (2012) estimate that IT adoption reduces mortality for the most severely ill Medicare enrollees but has little impact on those with mean severity. Agha (2012) finds that hospital IT adoption does not improve hospital mortality rates for Medicare enrollees.

[3] Prior to 2002, Medicare reimbursements partially covered hospital capital (but not labor) expenditures (Acemoglu and Finkelstein, 2008). The presence of this subsidy could spur hospitals to make significant investments in health IT, however, this capital investment subsidy ended prior to the period when the widespread diffusion of sophisticated EMR and Computerized providers order entry (CPOE) systems began.

[4] Motivated by the approach of Brynjolfsson and Hitt (1996), recent work estimates the productivity impact of health IT using discrete measures of health IT component adoption (e.g., EMR). Parente and Van Horn (2007), Borzekowski (2009), and Housman et al. (2010) estimate production and cost functions in a fixed effects framework. In each paper, IT was found to create modest efficiency gains. Dranove et al. (2012) find that the effect of EMR adoption may result in short-run cost increases but that long-run consequences depend upon market structure.

and revenue management, they are also designed to increase clinical quality. As discussed above, hospitals face significant challenges translating increased quality of care into higher revenues. This divergence between social and private benefits may lead to an underinvestment in quality.

In order to understand the impact of health IT on hospital productivity, we estimate the parameters of a value-added hospital production function where we decompose the hospitals' key productive inputs into conventional and IT categories. In our analysis, the productive inputs are labor, capital, health IT labor, and health IT capital. A well-known challenge to estimating production function parameters is that inputs are endogenous to unobserved (by the econometrician) productivity shocks (Marschak and Andrews, 1944; Ackerberg et al., 2007, Ackerberg, Caves, and Frazer, 2006). Over the last decade and a half, several different approaches have been proposed to correct for the endogeneity of input choice, including Olley and Pakes (1996), Blundell and Bond (1998), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2006). These approaches are differentiated regarding assumptions on the evolution of multifactor productivity (MFP) and in the timing of input choices. We employ each of these strategies but emphasize parameter estimates generated using the dynamic panel data (DPD) approach (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998, 2000). By using a variety of approaches we assess the robustness of our estimates. Ultimately, our primary conclusions are not sensitive to our focus on the DPD approach.

These more recently developed techniques leverage additional sources of identification and possess greater dynamic flexibility than traditional fixed effect strategies. However, in our setting these approaches come at a cost as we cannot allow for differences in effects across IT applications. This distinction is particularly important for studies of health IT and quality as clinical benefits almost certainly depend on the presence of EMR and complementary technologies such as computerized provider order entry (CPOE). Efficiency gains, however, may be realized from a wide range of IT inputs with both clinical and administrative functionalities. Although we believe that this broader measure of IT inputs is appropriate for studies of hospital productivity, we do explore the potential for the benefits from health IT to vary across investment levels, settings, and time.

We employ data from California's Office of Statewide Health and Policy and Development (OSHPD) for the 11-year period encompassing 1997–2007. The OSHPD data are well -suited to examine the productivity impact of health IT as they include detailed, hospital-specific information on health IT expenditures and depreciation, which we use to construct measures of the dollar value of health IT capital. We know of no other data set that has this detailed financial and health IT expenditure information. This period saw a rapid diffusion of health IT, and, over the span of our data, hospitals dramatically increased their IT investments. The average hospital expanded its IT capital stock by approximately 220% over the 11-year span of our data. We supplement these data with information on the specific health IT components adopted by hospitals from the Health Information Management Systems Society (HIMSS).

In addition to its health policy relevance, hospitals are an attractive setting to study the impact of IT investments on organizational productivity. Hospitals are one of the largest industries in the US, accounting for 5.3% of GDP and they are an industry in which technological change has a large impact on costs and consumer welfare (Cutler, 2004). Hospitals are complex, hierarchical, compartmentalized, and labor-intensive organizations where information creation and dissemination is central to their operations. Inpatient care requires the coordination of activities across many workers with diverse skill levels in which errors are potentially costly to both the hospital and the patient. Hospitals have well-documented challenges managing their information (Institute of Medicine, 1999). Because of this complexity, hospitals are an environment in which IT has the potential to significantly improve work flow, communication, and coordination.

The large literature studying the productivity impact of IT adoption principally analyzes data generated prior to 2000—a period when the PC revolution was of central interest to this literature (Tambe and Hitt, 2012).[5] Our analysis focuses on a recent period of time when new ITs were rapidly and broadly diffusing, providing an excellent environment to study the impact of recently developed IT.[6] Furthermore, most previous work on IT productivity uses data spanning broad classes of industries and types of organizations with a focus on very large firms. Because we study a single type of organization, acute-care hospitals, we eliminate an important source of unobserved heterogeneity that might affect cross-industry studies. Although hospitals are broadly homogeneous over the types of services they provide, they are heterogeneous with respect to size and ownership structure, so we can examine how these organizational differences affect the impact of health IT.

We find that both health IT capital and labor have high private marginal products—increases in health IT significantly increase hospital value-added. At the median, the net marginal product of IT capital is approximately \$1.04, and the net marginal product of IT labor is about \$0.73. These estimates imply that marginal increases in health IT can generate substantial increases in output. However, the absolute contribution of IT investments are small and diminishing. From 1997–2007, average hospital value-added increased 156%, about 6% is attributable to investments in health IT capital and labor. Unless there is a dramatic change in the state of health IT (which is certainly possible), our estimates imply that the large expected increase in hospitals' IT capital stock will have a modest impact on value-added output.

Network externalities are a classic reason for the divergence between public and private benefits from technology adoption (Katz and Shapiro, 1986). Network externalities have been found to affect technology adoption directly, through interoperable technologies, and indirectly through learning spillovers. We directly test for the presence of network externalities from competing hospitals in productivity using an identification strategy similar to Gowrisankaran and Stavins (2004). We find no evidence of meaningful network externalities in hospitals' health IT investments.[7]

Our data also allow us to examine three important ancillary questions: (i) Is there differential behavior between for-profit (FP) and not-for-profit (NFP) hospitals in their IT investments? (ii) Are vintage or learning effects in health IT important? (iii) What is the role of the change in multi-factor productivity in the increase in hospital value-added?

We also find that FP hospitals invest less in overall health IT and are less likely to adopt CPOE technologies. However, production function estimates indicate little difference between FP and NFP hospitals' abilities to translate health IT investments into productive output. As for our second ancillary question, the parameter estimates hint that later health IT investments are more productive than investments made at the beginning of our sample whereas the employment of health IT labor is significantly more productive in the last half of our time frame than in the first half. Finally, we find that increased hospital productivity from 1997–2007 is entirely driven by increased inputs.

The rest of this article has the following structure. The next section provides some institutional background on hospital IT. Section 3 describes our empirical model and Section 4 discusses our data sources. Section 5 discusses the basic patterns in the data and trends in health IT adoption. Section 6 presents and discusses the production function estimates. Section 7 concludes.

2. Background—hospital information technology

■ Hospitals began investing in health IT during the 1960s. Information technology was first used to support billing and financial services. Subsequently, the role of IT grew to manage pharmacy, laboratory, and radiology service lines (Collen, 1995). Although their primary purpose

[5] A classic article in this literature is Brynjolfsson and Hitt (1996).

[6] Tambe and Hitt (2012), Bloom, Sadum, and Reenen (2012), and Bartel, Ichniowski, and Shaw (2007) are three notable exceptions to the literature's focus on firm-level data prior to 2000.

[7] A recent survey of hospital health IT adoption asked about factors inhibiting adoption and the responses did not point to network externalities (Jha et al., 2008).

was to support billing and capture revenues (commonly referred to as charge capture) these applications began to monitor and support basic clinical activities. These systems frequently provided services such as pharmacy and laboratory process management as well as documentation of patients' radiology histories. These systems were nearly ubiquitous by 2000 (McCullough, 2008).

The development of EMR systems has greatly expanded the automation of clinical services. These systems replace a hospital's medical record and integrate clinical information from ancillary services such as pharmacy, radiology, and laboratory. More sophisticated systems allow physicians to directly access the electronic medical record and enter orders electronically. Computerized providers order entry (CPOE is intended to reduce communication errors and serve as a platform for treatment guideline automation. Although leading academic medical centers have been developing these technologies for many years, it is only during the past decade that these technologies began to diffuse widely.

Information technology can affect hospital productivity through a variety of mechanisms. Although hospitals may gain the same benefits from IT as any other service firm (e.g., improved supply chain management or enhanced labor productivity), three mechanisms are particularly important for hospitals: billing management, provider monitoring, and clinical decision support.

Improved billing may be the most widespread effect of hospital IT investments. Hospitals provide a wide range of services, and the prices of these services depend upon patients' clinical characteristics as well as contracts negotiated between payers and providers. For example, the reimbursement rate for cardiac surgery often depends upon whether a patient is a diabetic or has hypertension, as these comorbidities affect hospital costs. Price schedules and clinical documentation requirements depend on contracts with private insurers as well as government regulations. Although hospitals have long employed conventional IT for billing support, EMRs are increasingly used to document care and facilitate charge capture.

Clinical complexity also creates a difficult monitoring problem. Although physicians control most hospital resources, their actions are difficult to document and evaluate. Furthermore, most physicians are employed by physician-owned practices rather than hospitals. Hospitals use IT to monitor physician behavior. Relatively simple clinical information systems may be used to generate periodic reports on physician behavior and resource utilization. These reports may be used to support quality improvement initiatives or to identify the overuse of laboratory and radiology resources. Comprehensive EMR systems allow for much more sophisticated provider monitoring and may lead to improved resource allocation within hospitals.

Clinical decision support is the most ambitious objective of hospital IT. Sophisticated EMR systems with CPOE may be used as a platform to implement treatment guidelines, identify dangerous drug interactions, or coordinate care across provider team members. These real-time decision support functions should standardize care and reduce errors, thus enhancing both clinical quality and productivity.

Decision support systems are more effective when they possess detailed information regarding patients' clinical characteristics and treatment histories. Thus, EMRs may exhibit network externalities as their value could increase if neighboring providers adopted interoperable EMRs. Although many hospitals engage in information exchange, only 14% of California hospitials electronically exchange medical record information with competing hospitals by the end of our study period.[8]

Most of these productivity-enhancing mechanisms should be captured by conventional measures of value-added. Quality changes may, however, be omitted from value-added if they do not lead to increases in prices or quantities. This may be important for hospitals as quality is difficult to measure and the prices for many patients (i.e., Medicare beneficiaries) are fixed by law.

[8] Based on the 2007 AHA Annual Survey Information Technology Supplement.

3. Empirical strategy

■ We model value-added output for hospital i in period t (Y_{it}) as determined by a Cobb-Douglas production function whose inputs are conventional labor (L_{it}), conventional capital (K_{it}), IT labor (L_{it}^c), IT capital (K_{it}^c), and an unobservable (to the econometrician), ϵ_{it}.[9,10] We use lowercase variables to denote logarithms of inputs and the vector x_{it} comprises the entire set of logged hospital inputs. The starting point for our analysis is the following value-added production function:[11]

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \delta_l l_{it}^c + \delta_k k_{it}^c + \epsilon_{it}, \tag{1}$$

where β_l, β_k, δ_l, and δ_k are output elasticities of their respective inputs. We are primarily interested in the δ's which measure health IT's contribution to output. Hospitals may possess information on ϵ_{it} when selecting their inputs. We decompose this unobserved term into four components:

$$\epsilon_{it} = \alpha_i + \gamma_t + \omega_{it} + \eta_{it}. \tag{2}$$

The first term, α_i, is a time-invariant hospital fixed-effect while γ_t is a common, time-varying productivity shock. Both α_i and γ_t may be correlated with the inputs. The unobserved (to us) productivity term, ω_{it}, evolves according to an autoregressive process and may be correlated with observed inputs. Finally, η_{it} is a productivity shock that may be correlated with input choices and may evolve according to a moving average process.[12]

Correlation between the inputs and ϵ_{it} implies that standard approaches to parameter estimation will be biased. The appropriate econometric approach to remove the bias depends upon assumptions regarding the variation in α_i, the evolution of ω_{it}, and the timing of input selection (Ackerberg, Caves, and Frazer, 2006). Consequently, we estimate the parameters of (1) under several different assumptions over α_i and ω_{it} and compare these estimates to assess the robustness of our conclusions to different functional form and identification assumptions. Our primary model is the dynamic panel data (DPD) approach of Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998, 2000). The DPD approach is attractive in our setting as it allows for a time-invariant fixed-effect in the evolution of unobserved productivity. Many hospital characteristics such as its location and religious affiliation are time-invariant, whereas other aspects of hospital productivity (e.g., physician affiliation and reputation) evolve over time. Thus, the DPD framework better fits our institutional setting and provides internally consistent sources of variation that can be used to identify the parameters. Finally, the DPD approach is more robust to input measurement error.

Returning to equations (1) and (2), assume that ω_{it} evolves according to the following autoregressive process, $\omega_{it} = \rho\omega_{it-1} + \xi_{it}$, where ξ_{it} is an iid random shock. The key assumption is that the innovation in unobserved productivity, ξ_{it}, is uncorrelated with $x_{is} \forall s \leq t$. Although ϵ_{it} contains a hospital fixed-effect as well as an evolving productivity component, it may be

[9] This section draws heavily upon the work of Ackerberg, Caves, and Frazer (2006).

[10] We measure output using value-added, a common measure of output in productivity studies (e.g., Levinsohn and Petrin, 2003). That is, y_{it} is operating revenues net of all intermediate inputs. We use this output measure for two reasons. First, hospitals produce multiple products, and these must be aggregated into a single output measure. In effect, value-added aggregates across many different services weighted by the revenue associated with that service. Second, production is heterogeneous across hospitals. The value-added production function accounts for aspects of quality reflected in market prices and quantities.

[11] The IT productivity literature primarily employs the Cobb-Douglas production function in their analyses (Brynjolfsson and Hitt, 1996, 2003; Stiroh, 2002), and it is the specification of choice in dynamic panel environments (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998, 2000). We follow this literature and assume a Cobb-Douglas production relationship. However, it is well known that the Cobb-Douglas function imposes strong parametric relationships on marginal products, a relationship that we are particularly interested in quantifying in this article. We have explored using a less restrictive trans-log production function and the estimates did not reject the Cobb-Douglas specification.

[12] The assumed properties of ω and η differ across DPD, OP, LP, and ACF models. We first describe their properties for DPD models but discuss how these assumptions differ for other models below.

correlated with x_{it}. Solving for ω_{t-1} and substituting into (1) yields the dynamic factor (common factor) representation:

$$y_{it} = \rho y_{it-1} + \beta_l l_{it} - \rho\beta_l l_{it-1} + \beta_k k_{it} - \rho\beta_k k_{it-1} + \delta_l l^c_{it} - \rho\delta_l l^c_{it-1} + \delta_k k^c_{it} - \rho\delta_k k^c_{it-1} + \gamma_t - \rho\gamma_{t-1} + \alpha_i - \alpha_i\rho + \xi_{it} + \eta_{it}, \tag{3}$$

or

$$y_{it} = \pi_1 y_{it-1} + \pi_2 l_{it} + \pi_3 l_{it-1} + \pi_4 k_{it} + \pi_5 k_{it-1} + \pi_6 l^c_{it} + \pi_7 l^c_{it-1} + \pi_8 k^c_{it} - \pi_9 k^c_{it-1} + \gamma^*_t + \alpha^*_i + \xi_{it} + \eta_{it}, \tag{4}$$

where the common factor restrictions are $\pi_3 = -\pi_1\pi_2$, $\pi_5 = -\pi_1\pi_4$, and $\pi_7 = -\pi_1\pi_6$. Furthermore, $\alpha^*_i = \alpha_i(1-\rho)$ and $\xi^*_{it} = \xi_{it} + \eta_{it}$.

Assuming the common factor restrictions hold, OLS will yield consistent parameter estimates under the restrictive assumption that $E(\alpha^*_i x_{it}) = 0$, $E(\xi_{it} x_{it}) = 0$, and $E(\eta_{it} x_{it}) = 0$. Similarly, the fixed-effects estimator will generate consistent estimates if $E(\xi_{it} x_{it}) = 0$ and $E(\eta_{it} x_{it}) = 0$.

The DPD specification consistently estimates parameters under less restrictive assumptions than OLS and FE. We employ a system GMM approach that simultaneously estimates the equation of interest using both levels and differences specifications where appropriate lags of the levels and differenced variables can be used as instruments. Lagged levels are used as instruments for the differences equation, while lagged differences are used as instruments for the levels equation. This simultaneous estimation strategy results in lower finite sample bias and increased precision. Specifically, the DPD approach uses the following moment conditions:

$$E[\Delta x_{it-s}(\alpha^*_i + \xi^*_{it})] = 0 \quad \text{and} \quad E[\Delta y_{it-s}(\alpha^*_i + \xi^*_{it})] = 0, \quad \text{for} \quad s \geq 1 \quad \text{and} \quad t \geq 3, \tag{5}$$

$$E[x_{it-s}\Delta\xi^*_{it}] = 0 \quad \text{and} \quad E[y_{it-s}\Delta\xi^*_{it}] = 0, \quad \text{for} \quad s \geq 2 \quad \text{and} \quad t \geq 3. \tag{6}$$

Values of t and s are determined by the assumption on the autocorrelation structure in η_{it}. This assumption can be validated by testing whether the first differenced residuals' exhibit second-order serial correlation. The specification tests indicated that $s = 3$ removes the serial correlation and is used in the estimation. As the model is overidentified, we employ the Hansen test for instrument validity.

For robustness purposes we also estimate the parameters in (1) using the econometric strategies of OP, LP, and ACF. At one level, these three models are similar to each other as they employ two-step estimators using proxy variables to control for the productivity shocks, thereby removing bias. At another level, these three models make very different assumptions on both the proxy variable and the timing of input decisions, which may have large implications for identification (Ackerberg, Caves, and Frazer, 2006). Specifically, OP uses investment as the proxy variable while LP uses material inputs and ACF considers using both investments and material inputs as proxies. We first focus on the ACF approach and then discuss both LP and OP.

Returning to equation (2), ACF/OP/LP assume that $\epsilon_{it} = \omega_{it} + \eta_{it}$. The hospital fixed-effect is dropped from this specification while a first-order Markov process governs the transitions of ω_{it} between periods t and $t+1$. That is, $p(\omega_{it+1}|I_{it}) = p(\omega_{it+1}|\omega_{it})$ where $p(\cdot|\cdot)$ denotes the density function and I_{it} is the information set. Under ACF, labor and capital (both conventional and IT) are assumed to be chosen prior to period t. Given these assumptions, the hospital's materials input demand, m_{it}, is given as $m_{it} = f(\omega_{it}, l_{it}, k_{it}, l^c_{it}, k^c_{it})$. Inverting this equation and substituting back into (1) and (2) yields

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \delta_l l^c_{it} + \delta_k k^c_{it} + f^{-1}(m_{it}, l_{it}, k_{it}, l^c_{it}, k^c_{it}) + \eta_{it}. \tag{7}$$

The β's and δ's are not separately identified in equation (7). ACF's strategy is to estimate $y_{it} = \Phi(m_{it}, l_{it}, k_{it}, l^c_{it}, k^c_{it})$ nonparametrically in a first stage. We estimate Φ using a second order polynomial. In the second stage, estimates of $\omega_{it}(\beta_l, \beta_k, \delta_l, \delta_k) = \hat{\Phi} - \beta_l l_{it} - \beta_k k_{it} - \delta_l l^c_{it} - \delta_k k^c_{it}$

are constructed. ω_{it} is then nonparametrically regressed on ω_{it-1} and η_{it} is calculated. Production function parameters are then identified from the following moment condition:

$$E(\eta_{it} \cdot z_{it}) = 0, \tag{8}$$

where $z_{it} = (l_{it-1}, k_{it}, l^c_{it-1}, k^c_{it})$. Since η_{it} is the iid portion of the error term, inputs z_{it} were chosen before this period t productivity shock.

We also estimate the parameters using the LP and OP approaches. Both LP and OP assume that l_{it} is chosen knowing ω_{it}. This implies a different moment condition in which contemporaneous labor replaces lagged labor in (8). LP use materials (inputs excluding capital and labor) as the proxy variable while OP uses investment. Those differences may be important depending on the distribution of investment and the underlying reasons for the lag in the timing of input choices.[13] Both approaches identify the labor coefficients in the first stage. The LP moment condition used to identify the capital coefficient replaces m_{it-1} for l_{it-1} whereas the OP moment condition is simply $E(\eta_{it} k_{it}) = 0$. Although the LP and OP approaches have been widely used, ACF notes that they face potential identification problems due to the collinearity in input choices. ACF further argue that this concern does not apply to their approach.

There are distinct advantages and disadvantages of the DPD and the ACF/LP/OP approaches. As discussed above, an advantage of the DPD approach in our setting is that it allows for a time-invariant hospital fixed-effect. The DPD approach is also consistent with more complex models of input demand frictions (e.g., adjustment costs or labor shortages) and can accommodate multivariate productivity shocks while ACF/LP/OP place more restrictions on the underlying input demand model. ACF/LP/OP require a univariate unobservable productivity shock and input demand must be monotonic in ω_{it} for at least one input. For example, in an adjustment cost framework input demand is a function of lagged values of the productivity shock and this is not consistent with the ACF framework (Bond and Soderbom, 2005). Conversely, the DPD approach imposes a linear autoregressive structure on the evolution of ω_{it}, while ACF/LP/OP allow ω_{it} to follow an arbitrary first-order Markov process. ACF/LP/OP estimate Φ nonparametrically. Finally, DPD is likely asymptotically less efficient than ACF/LP/OP.

Each of the above estimation approaches has clear advantages and disadvantages. Furthermore, there are no obvious specification tests for determining which model is most appropriate. ACF recommend examining the robustness of parameter estimates using several different approaches. Although we emphasize the DPD model, all four estimation strategies are employed to assess the sensitivity of parameter estimates to different identification assumptions.

□ **Identification.** The different estimators rely on different sources of variation for identification. ACF/LP/OP approaches rely on both cross sectional and over time variation in input uses that are assumed to be orthogonal to shocks to inferred innovation in ω_{it}. This variation is assumed to be driven by shocks that differentially affect input choices through the models' assumptions on the timing on input adjustments. Importantly, if there are exogenous shocks that differentially affect hospitals' input uses those shocks can be relied upon to help identify parameters.

The DPD approach primarily relies on within-hospital variation in input use to identify parameters. This is a more restrictive source of variation, however, the DPD approach is internally consistent with a broader set of explanations for input variation. In particular, the DPD model is consistent with input use variation driven by adjustment costs to all inputs—a plausible explanation of the within variation of input use in our setting. Because the DPD approach leans heavily on within-hospital variation for identification, it requires a long panel with significant within variation in inputs. Fortunately, we possess a long panel of hospitals (11 years) and, as we discuss below and in Sections 4 and 5, there is meaningful within and cross sectional input use variation.

[13] LP point out that if there is a mass point in investment at zero (which is common for smaller firms), the necessary inversion of the f function does not exist. In our case this is not important as hospitals always make positive investments in our data.

The California regulatory environment provides an impetus for further input variation. In 2004, California implemented mandatory nurse staffing ratios for hospitals which required hospitals to maintain a minimum number of nurses per inpatient. These regulations were phased in over time. Prior to the legislation most hospitals did not meet the requirements and had to increase their labor inputs to comply with the regulation (Spetz et al., 2009). This regulation differentially affected hospitals as there were prelegislation differences across hospitals in nurse staffing ratios. Standard models of input demand imply that exogenous changes in one input will affect the demand for other inputs. This combined with the rise in health IT use, which also varies across hospitals, facilitates relatively cleaner identification of production function parameters.

More broadly, examining correlations between inputs and outputs through the lens of a production function has advantages and limitations. First, the production function framework allows for sources of both endogeneity and identification that are consistent with economic theory. Second, this approach generates parameter estimates with specific theoretical interpretations. This is important when decomposing the determinants of productivity and exploring the implications of counterfactual input levels.

There are, however, notable limitations to imposing a formal production function structure on the data. As a practical matter, our approach cannot allow for heterogeneity in IT capital inputs. Similarly, our approach only captures the effects of inputs on value-added. These issues may be particularly important when studying the relationship between health IT and quality. Although a relatively small number of IT applications should directly affect quality, many applications are likely to effect productivity; furthermore, we restrict our interpretation to effects on value-added. The production function framework also places strong functional form and behavioral assumptions on the data-generating process and assumes that the direction of causality is from inputs to outputs. For example, market imperfections such as liquidity constraints can induce a reverse causation between inputs and outputs and, if important, can lead to biased inference.[14] This highlights the need for valid identification assumptions. Where possible we have attempted to test for violations of the underlying production function and identification assumptions and believe that the advantages of our approach outweigh its potential shortcomings in this setting.

□ **Ownership differences, network externalities, and vintage effects.** In addition to estimating the impact of IT inputs on productivity, we explore other dimensions of the data to better understand the underlying relationship between IT and value-added. There are five areas of interest: the impact of for-profit status, network effects, vintage effects, technological complementarities, and the impact of hospital size.

Not-for-profit and for-profit hospitals may have differing organizational objectives which lead them to use IT differently. There is a long literature examining the differential behavior of for-profit and not-for-profit hospitals.[15] This body of work typically finds little difference in behavior across these organizational forms. However, more recent research points to for-profit hospitals investing in more profitable services and avoiding the least profitable services relative to their not-for-profit counterparts (Horowitz and Nichols, 2009; David et al., 2011). If hospitals cannot appropriate a significant portion of the returns to IT investments and if NFPs have different long-run objectives than FPs, then IT investment strategies should differ across ownership forms. Differential investment behavior across ownership forms could have meaningful policy implications such as justifying the tax-exempt status of not-for-profit hospitals. To explore whether the productivity of IT investments differs across ownership form, we split the sample and estimate production function parameters separately for each hospital type.

A classic explanation for the divergence between public and private benefit of IT is network externalities (Katz and Shapiro, 1986). Network externalities have been found to affect technology

[14] Lee and McCullough (2012) test for evidence of liquidity constraints in investments and find no evidence that California hospitals' IT investments are liquidity constrained during our sample period.

[15] See Sloan (2000) for an excellent review of the literature on the role of ownership status and provider behavior.

adoption directly, through interoperable technologies, and indirectly through learning spillovers. There is, however, little empirical evidence regarding network effects in the productive value of health IT. As discussed in Section 2, cross-provider information sharing is argued to be an important driver of health IT value. Furthermore, hospital adoption of health IT could affect neighboring providers' IT adoption and IT value either directly or indirectly. We test for the presence of network externalities from competing hospitals in health IT productivity using an identification strategy similar to Gowrisankaran and Stavins (2004) in which fixed-effects control for time-invariant, unobserved heterogeneity that affect the firms' and neighbors' adoption.[16]

To implement the test for network externalities, we construct measures of neighboring hospitals' IT input use. For each hospital, local markets are defined as other hospital institutions in a 30-mile radius.[17] Market-level IT input utilization measures are based on neighboring hospitals' average IT capital and IT labor inputs. These measures are weighted by the number of staffed inpatient beds. These variables are then added to the base specification and treated as potentially productive inputs and the parameters are estimated using DPD methods. The DPD framework also allows us to address potential time-varying sources of endogeneity in competing hospitals' adoption of IT by instrumenting for IT inputs using lagged levels and lagged differences in competing hospitals' IT input utilization.

Health IT's value may also change over time. Technological innovation could, for example, increase the value of more recent IT investments. This may be particularly important as innovation helped spur the rapid diffusion of EMR and CPOE systems during our study period. Conversely, learning may increase the value of older IT investments as hospitals train staff or adjust work flows when implementing new information systems. We employ several approaches to explore these issues. First, we divide the data into pre- and post-2002 subsamples and estimate parameters for each period separately. We also estimate models that allow for higher-order autocorrelation in IT inputs.

Health IT may exhibit increasing returns to IT investments. Electronic medical records could, for example, be complementary to CPOE investments. Imperfect scalability in hardware and software investments may cause returns from IT to increase in the size of IT investments. Consequently, we separate our sample into two groups based on whether the hospital's final observed IT capital level exceeded the median.

Finally, larger hospitals may utilize health IT more effectively as the benefits of managing large amounts of patient data plausibly increases in the size of the hospital. In order to examine this possibility, we divide the sample in half based on hospital bed size (median = 173 beds) and estimate the production function parameters separately for each group of hospitals.

4. Data

■ Our primary source is the Office of Statewide Health Planning and Development (OSHPD) data from 1997 to 2007. These data contain detailed annual financial and productivity information for the vast majority of California hospitals. They also contain hospital characteristics such as bed size and ownership. We supplement these data with the Health Information Systems Society (HIMSS) Analytic survey from 1998–2007. The HIMSS data contain detailed information on the specific applications adopted by hospitals. The HIMSS data serve as a window into the specific IT strategies that hospitals employ.

Our sample comprises 309 short-term, acute care, nonfederal, California hospitals. The Kaiser Permanente hospitals are excluded as they do not report detailed hospital-level financial

[16] We do not test for network externalities across potentially complementary providers (e.g., physicians) in the adoption of health IT.

[17] We also examine the robustness of our results using alternative radii and Health Services Areas (HSAs) as our market definitions. Results are robust to these different measures. Market areas were constructed using BatchGeo's geocoding service and confirmed via USC WebGIS Services (Goldberg and Wilson, 2010). The HSA definitions are available from *The Dartmouth Atlas of Health Care* (Dartmouth Institute for Health Policy and Clinical Practice).

data to OSHPD.[18] The OSHPD data include detailed balance sheet, income statement, and other financial as well as non-financial information.[19] Hospitals are required by California law to report this information and OSHPD make these data publicly available.[20]

We operationalize our output measure, value-added, as operating revenues less intermediate inputs. Intermediate inputs include surgical supplies, linens, clothing, and other material inputs. Intermediate inputs do not include labor and capital measures. These inputs are captured by the Supply variable among Total Operating Cost in OSHPD's Trial Balance Worksheet and Supplemental Expense Information. Conventional (non-IT) capital is defined as total assets, including Current Assets, Property, Plant and Equipment, Intangible Assets, Assets whose use is limited, and Other Assets. Naturally, IT capital inputs were excluded from the conventional capital measure. Conventional (non-IT) labor is defined as the total conventional Salaries, Wages, Employee Benefits, and Professional Fees.[21]

A unique aspect of the OSHPD data is that it tracks hospital IT expenditures by input category. That is, we can formulate measures of both IT capital and labor. The OSHPD data place all IT expenditures within financial statements' data processing sections. For our purposes, information technology labor is the summation of Salaries and Wages, Employee Benefits, and Professional Fees associated with data processing. Information technology capital is a summation of four components: Purchased Services, Leases and Rentals, Other Direct Expenditure, and Physical Capital, respectively. Leases and Rentals represent IT capital such as software licensing payments. Purchased Services are payments for outsourced IT such as application service provision.[22] Physical capital is the quantity of IT capital stock at a specific time whereas the previous three categories are flow measures. A complication for the construction of health IT capital is that OSHPD does not directly report the stock of physical IT capital but only reports flow expenditures on IT capital in each given year. We therefore construct the stock of health IT physical capital using the reported IT investments. The Modified Accelerated Cost Recovery System (MACRS) specifies that computers and information systems are depreciated over a five-year period.[23] We use a five-year linear deprecation schedule in order to construct the annual physical IT capital stock for each hospital in our data.[24] Our IT input measures were confirmed with data from HIMSS, which occasionally included analogous questions within their survey.[25]

In order to assess the validity of our IT capital measure we examine its relationship to the discrete measures of health IT adoption.[26] To do this we regress the logarithm of IT capital on indicators of three different health IT adoption measures (EMR, CPOE, and PACS), hospital control variables (logarithm of beds size, ownership status indicators), and annual dummies. All parameters on health IT variables are positive and account for a large portion of the variation in

[18] These 16 Kaiser hospitals are part of a vertically integrated managed care organization that includes health plans, employed physicians, and other health care providers; consequently, they were exempted from the reporting requirements faced by other hospitals.

[19] There were a modest number of missing values which were imputed via *hot deck* and stratified by bed size and ownership type.

[20] The data are available at www.oshpd.ca.gov/HID/DataFlow/HospFinancial.html.

[21] Our measure of labor inputs also include the labor intensive inputs of Daily Hospital Services, Ambulatory Services, Ancillary Services, Research, Education, General Services, Fiscal Services, and Administrative Services.

[22] We recognize that purchased services likely include both capital and labor inputs. Although the data do not provide the detail necessary to disentangle the component inputs, qualitative work suggests that this is mostly a capital measure. We test our results for sensitivity to this assumption.

[23] Economic depreciation of IT assets would be better described as a capital loss due to technological obsolescence and is likely more rapid (e.g., over four years). For constructing our IT capital measure, it is accounting depreciation rather than actual depreciation that matters.

[24] We use data from the years 1993–1996 to calculate the initial period IT capital stock.

[25] Results are also robust to alternative depreciation schedules. Specifically, we estimate the DPD model using a four-year depreciation schedule and the parameter estimates were essentially identical to our base model estimates.

[26] The adoption of individual IT systems requires non-trivial expenditures pre- and post- installation and thus fixed effects approaches to correlating IT capital and IT system adoption will likely underestimate the true underlying correlation.

IT capital. Adoption of all three IT components is associated with an approximately 60% increase in IT capital. We reject the joint hypothesis that all IT coefficients are zero at the 1% level.[27] That is, our measure of IT capital correlates with hospital adoption of costly IT systems. To assess the correlation of value-added to these discrete IT adoption measures we regress value-added on EMR, CPOE, and PACS indicators in a FE framework controlling for capital and labor inputs.[28] The adoption of IT systems is correlated with an increase in value-added. The estimates indicate that the adoption of all three IT systems leads to an approximate 6.5% increase in value-added–the coefficients are jointly significant at the 5% level.

As we construct our measure of health IT capital using investment information and assumptions on depreciation, it is possible that this measure systematically under- or over-represents the true IT capital for the hospital. This issue is not unique to our setting as most productivity analyses rely on accounting information which will embody assumptions on depreciation and expenditure classification. An obvious question then is, how will our estimators perform given this possible measurement error?

As is well known, in iid measurement error settings the coefficients from OLS and FE will be biased toward zero. If our measure understates capital, then the OLS parameters will be biased upwards. The opposite is true if IT capital is overstated. Measurement error also negatively affects the OP and LP estimators. In order to perform the necessary inversion, OP and LP require that ω is the only unobservable in investment and material inputs functions, respectively. The nonlinear nature of the mapping between the unobservables and the proxy variable makes signing the bias difficult. One advantage of the DPD estimator and one of the reasons it is our preferred specification is that it likely performs better than LP and OP if our input measures, particularly IT capital, suffer from either iid or systematic measurement error. For example, if we systematically underestimate hospitals' IT capital and that degree varies by firm, then this error will be incorporated in the hospital fixed effect, which is controlled for in the estimation algorithm. If the measurement error is iid, the instrumenting strategy of DPD estimator should reduce the downward bias. Of course, DPD approaches require sufficient within-hospital variation in inputs which, as we document below, is the case.

5. Trends and summary statistics in health IT adoption

■ Figure 1 displays the trends in IT capital stock and IT labor inputs per bed for our sample of hospitals. Information technology capital and labor inputs increased steadily from 1997–2007. Over this timeframe, IT capital stock grew almost threefold to over $35,000 per staffed bed in 2007. The employment of IT labor also grew but less rapidly than IT capital. Between 1997–2007, on average, hospitals' IT labor inputs more than doubled.

Descriptive statistics are provided in Table 1. Mean values of Y_{it}, L_{it}, K_{it}, L^c_{it}, and K^c_{it} are provided in both levels and shares relative to value-added.[29] Several patterns in the summary statistics are worth highlighting. First, health IT capital inputs increased dramatically over this period, both in absolute and relative terms. Average health IT capital grew 220% and as a percentage of value-added grew from 3.6% to 4.5%. Information technology labor inputs grew 213% over this period, and its share relative to value-added increased marginally.

Not-for-profit hospitals constitute 55% of the sample while for-profit and government-owned hospitals comprise 25% and 20%, respectively. On average, FP hospitals are significantly smaller than NFP and government hospitals. There are also meaningful differences across ownership forms in the use of health IT. For-profit hospitals utilize fewer IT inputs but more conventional capital per dollar of output than NFP hospitals. The relative growth rate of health IT capital for FPs is also notably lower than NFP hospitals. This suggests that either FPs have different

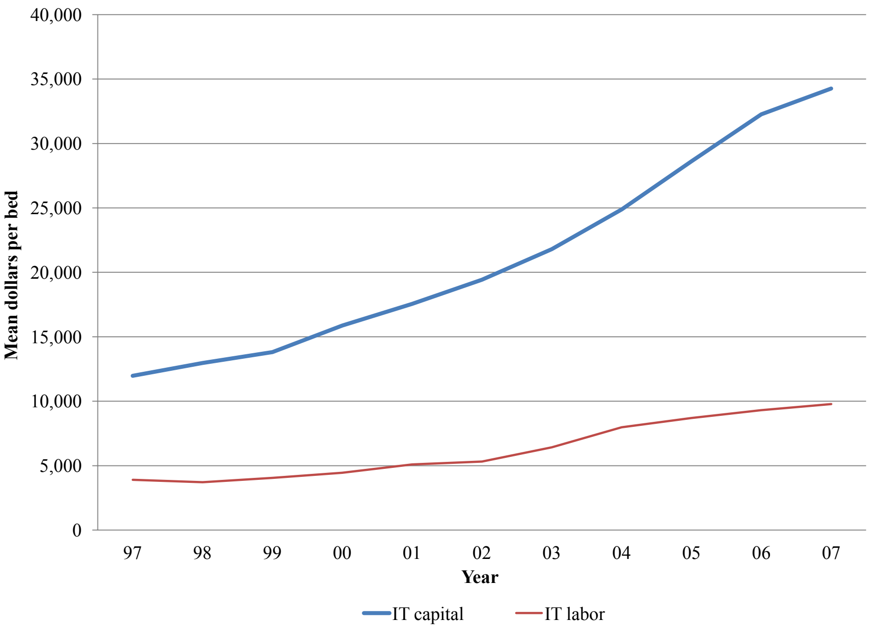
[27] These regression results are available from the authors upon request.

[28] OP, LP, and ACF models cannot be estimated with discrete inputs as the monotonicity assumption is violated.

[29] The variables are converted to 2007 dollars using the GDP deflater.

FIGURE 1

TRENDS IN IT CAPITAL AND IT LABOR PER BED



production technologies than NFPs, that they face different input costs, or that they have different objectives in their health IT utilization.

The HIMSS data allow us to examine patterns of health IT adoption for EMR and CPOE—two important health IT components that were diffusing during our time period. Figure 2 displays the time series of the percentage of hospitals that have adopted these platforms for the entire sample and separately for NFP, FP, and government hospitals. The figure shows that increases in IT capital are associated with increased adoption of these two technologies. As discussed above, this correlation between IT capital and health IT system adoption is present in the individual hospital data. EMR diffused much more widely than CPOE. By 2007, almost 50% of hospitals had adopted EMR whereas approximately 33% of hospitals had adopted CPOE. There are meaningfully different patterns of technology adoption between NFP and FP hospitals. FP hospitals began the period with a much lower EMR adoption rate, but by the end of the sample they had slightly higher EMR utilization levels. FP hospitals, however, continued to lag other hospitals in the adoption of more sophisticated systems with CPOE capabilities. These figures and the summary statistics suggest that, in fact, FP and NFP hospitals may have divergent strategic aims in their use of health IT. Our EMR measure differs notably from Jha et al. (2009) as they focus on comprehensive electronic health record systems. Our measure is similar to the enterprise EMR definition employed by Tucker and Miller (2011). Although the HIMSS data demonstrate that clinically relevant information systems are rapidly diffusing during our study period, it is not practical to employ these data directly in our analysis.[30]

Production function parameters are identified by dynamic variation in input choices (Ackerberg, Caves, and Frazer, 2006; Bond and Soderbom, 2005). The variation we leverage to identify the parameters is demonstrated by the means and standard deviations of hospital-specific long

[30] The discrete nature of the HIMSS application data cannot, for example, be incorporated into the OP, LP, or ACF models as the function could not be inverted. Although discrete data can, in theory, be employed in the DPD models there is only meaningful variation during the year of actual technology adoption. Finally, the detailed application-level data are not available for all years of our sample.

TABLE 1 Means and (standard deviation) in \$1,000 and Shares of Input As a % of Value-added

	Entire Sample							
Variable	*Total*	*Share*	*FP*	*Share*	*NFP*	*Share*	*GOV*	*Share*
Value-added (Y)	133,895	100.0%	74,892	100.0%	164,548	100.0%	124,326	100.0%
	(181,806)		(71,881)		(208,531)		(180,735)	
Labor (L)	117,851	88.0%	67,161	89.7%	145,031	88.0%	107,389	86.4%
	(151,530)		(60,158)		(173,742)		(149,212)	
Capital (K)	173,090	129.3%	81,171	108.4%	219,832	133.6%	150,844	121.3%
	(267,923)		(120,701)		(2314,255)		(234,095)	
IT labor (L^c)	1,576	1.2%	539	0.7%	2,025	1.2%	1,616	1.4%
	(3,146)		(903)		(3,793)		(2,678)	
IT capital (K^c)	5,537	4.1%	1,306	1.7%	7,823	4.8%	4,609	3.7%
	(11,206)		(1,757)		(13,866)		(7,723)	
Number of Hospitals	309		78		169		62	
1997								
Value-added (Y)	83,889	100.0%	35,110	100.0%	101,514	100.0%	81,528	100.0%
	(109,648)		(29,756)		(110,840)		(134,698)	
Labor (L)	72,889	90.5%	34,221	97.5%	88,836	87.5%	66,237	81.2%
	(86,476)		(30,292)		(89,668)		(99,023)	
Capital (K)	115,968	131.3%	38,218	108.9%	150,970	148.7%	95,479	117.1%
	(1452,400)		(41,421)		(172,165)		(132,141)	
IT labor (L^c)	867	1.0%	247	0.7%	1,108	1.1%	793	1.0%
	(943)		(268)		(2,027)		(1,228)	
IT capital (K^c)	3,013	3.6%	715	2.0%	4,156	4.1%	2,145	2.6%
	(5,239)		(1,123)		(6,371)		(3,058)	
Number of Hospitals	293		57		167		69	
2007								
Value-added (Y)	214,317	100.0%	115,876	100.0%	281,136	100.0%	159,184	100.0%
	(262,092)		(92,247)		(316,109)		(186,868)	
Labor (L)	193,456	90.3%	109,684	94.7%	241,869	86.0%	168,901	106.1%
	(223,600)		(81,550)		(257,135)		(215,093)	
Capital (K)	291,573	136.0%	126,601	109.3%	390,184	138.8%	233,344	146.6%
	(438,564)		(176,743)		(431,344)		(351,288)	
IT labor (L^c)	2,712	1.3%	914	0.8%	3,507	1.2%	2,794	2.1%
	(5,140)		(1,516)		(56,159)		(4,519)	
IT capital (K^c)	9,630	4.5%	2,333	2.0%	14,191	5.0%	6,543	4.1%
	(18,131)		(2,550)		(22,709)		(10,439)	
Number of Hospitals	298		74		161		63	

Note: NFP is not-for-profit; FP is for-profit; and GOV is government.

differences of the logged inputs (t = 2007 minus t = 1997). The means of the differences of the logarithms of the inputs are 0.88, 0.53, 0.80, and 1.15 and the standard deviations are 0.35, 0.65, 1.20, and 1.20 for L, K, L^c, and K^c, respectively. There is notable heterogeneity in input utilization for all inputs over this period.

6. Production function estimates

■ Production function estimates are presented in Table 2. The first two columns present OLS and FE estimates.[31] Parameters of the DPD model are estimated by system GMM and presented in column (3). The OLS and FE model estimates are almost all lower than the estimates in our base model. This is consistent with the large literature estimating production function parameters and the notion that input choices are endogenous. The DPD estimates indicate that IT capital and IT labor are very productive and the coefficients are significantly different from zero. Common

[31] Standard errors are clustered at the hospital level.

FIGURE 2

TRENDS IN EMR AND CPOE ADOPTION

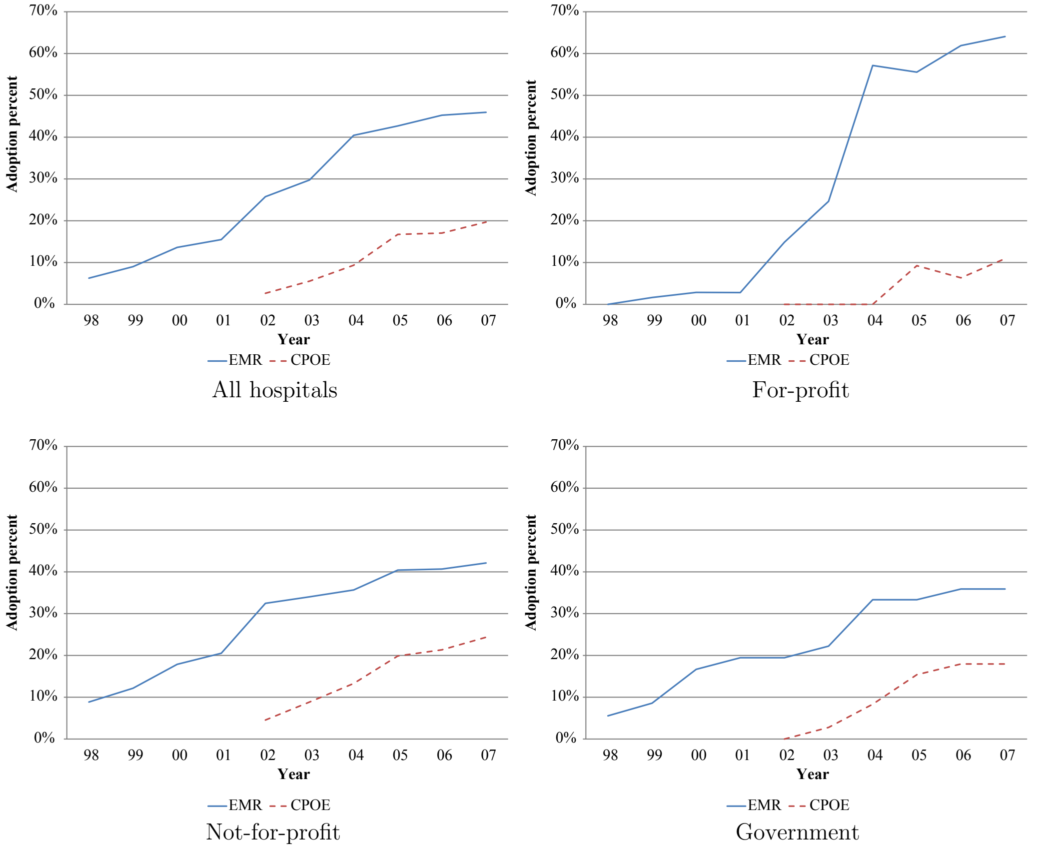


TABLE 2 **Production Function Parameter Estimates**

Variable	OLS (1)	FE (2)	DPD (3)	ACF (4)	OP (5)	LP (6)
Labor, l_t	.790**	.588**	.781**	.775**	.901**	.847**
	(.028)	(.070)	(.046)	(.028)	(.019)	(.024)
Capital, k_t	.096**	.0862**	.140**	.182**	.179**	.125**
	(.014)	(.014)	(.029)	(.025)	(.051)	(.036)
IT labor, l_t^c	.012**	.011**	.028**	.009**	.004	.003
	(.003)	(.002)	(.007)	(.003)	(.004)	(.004)
IT capital, k_t^c	.028**	.026**	.045**	.033**	.038**	.033**
	(.003)	(.004)	(.009)	(.005)	(.005)	(.005)
ρ	.799**	.555**	.664**	–	–	–
	(.028)	(.034)	(.046)			
ComFac	.000	.000	.218	–	–	–
No of obs.	2,904	2,904	2,904	3,392	3,392	3,392
No of hosp.	264	264	264	309	309	309

Note: OLS is ordinary least squares; FE is fixed-effects; DPD is dynamic panel data (Blundell/Bond); ACF is Ackerberg/Caves/Frazier; OP is Olley/Pakes; and LP is Levinsohn/Petrin. Standard errors are in parentheses. ** : $p < 0.01$.

factor restrictions are not rejected for the DPD model (they are rejected for the OLS and FE estimates), and the Hanson test p-value is .54 indicating that the overidentification restrictions are not rejected. Finally, parameter estimates do not reject a constant returns to scale technology.

The ACF, OP, and LP estimates are reported in columns (4), (5), and (6) of Table 2, respectively.[32] Parameter estimates from these models are generally lower than estimates from the DPD approach but still higher than OLS and FE estimates. Furthermore, standard error bands for the DPD, ACF, OP, and LP models generally overlap. Interestingly, ACF, OP, and LP parameter estimates for the IT variables are all very similar. There are, however, important differences across approaches in parameter estimates for conventional inputs. For example, the OP estimates imply increasing returns to scale while the ACF and LP estimates are consistent with constant returns to scale. Although broadly consistent with the ACF, LP, and OP estimates, the dynamic panel data model generates higher health IT elasticities and may be seen as the most optimistic of our parameter estimates in assigning value to IT inputs.

□ **Contributions of health IT to value-added.** We examine the implications of our production function parameter estimates on the historical contributions of hospitals' IT inputs to value-added and the forecasted impact of the broad health IT expansion contained in the HITECH Act. To measure the historical contribution of health IT, we calculate the difference in each hospital's implied value-added under 2007 and 1997 health IT input levels. Value-added grew an average of 156% over this period—an approximately 7% compound growth rate. Health IT capital grew an average of 220% over this period while IT labor grew by 213%. Combined, IT inputs accounted for a 6% increase in value-added output.

We use our parameter estimates to model the implied long-run net benefits of expanding IT inputs. The IT capital marginal product calculations depend on hospitals' opportunity cost of capital and on the rate of IT capital depreciation. We assume a nine percent opportunity cost of capital and four-year straight-line depreciation for IT capital inputs.[33] We first recovered hospital-specific productivity shocks, ϵ_{it}. Counterfactual simulations were then based on parameter estimates and actual input levels.

All estimation strategies yield high marginal products for IT capital inputs. Median long-run net marginal products range from \$0.73 (95% CI: [\$0.33, \$1.42]) for ACF to \$1.29 (95% CI: [\$0.48, \$2.22]) for DPD.[34] The net marginal product of IT labor ranges from \$0.006 (95% CI: [\$0.22, \$0.37]) for ACF to \$1.45 (95% CI: [\$0.33, \$2.65]) for DPD. The implied IT labor marginal products for OP and LP were negative but not statistically significant. These marginal products are similar to estimates of IT value in other industries. For example, Brynjolfsson and Hitt (1996) estimate a net marginal product of \$1.62 for IT labor and a long-run net marginal product of \$0.67 for IT capital.

Although the marginal effects of IT inputs are high, their absolute contribution to value-added is modest. Doubling IT capital inputs from 2007 levels would increase total value-added by less than 2% while doubling IT labor inputs would increase value-added by less than 1% for the median hospital. Both IT inputs exhibit high marginal benefits that diminish slowly. These results suggest that substantial increases in IT inputs would be beneficial.

The high marginal products for health IT could reflect either an underinvestment in IT or the cost of unmeasured complements. For example, Brynjolfsson and Hitt (2003) find that IT investments are correlated with MFP. This could be because software expenditures (a large

[32] Standard errors for the ACF, OP, and LP models are generated via bootstrap clustered at the hospital level using 200 draws.

[33] Outsourced IT goods and services are treated as flow inputs. We reach similar conclusions when varying the cost of capital or depreciating IT capital over a three- to five-year period. We also explore alternative models that estimate separate parameters for owned and outsourced IT. Our overall conclusions are consistent with these alternative assumptions.

[34] These estimates are based on 2007 input levels. The results are, of course, sensitive to assumptions about depreciation; for example, a three-year useful life would decrease the long-run marginal product by about 25%.

TABLE 3 DPD Estimates By Ownership Type and Tests for the Presence of Network Effects

Variable	FP (1)	NFP (2)	Government (3)	Network effects (4)
Labor, l_t	.896**	.597**	.441**	.830**
	(.042)	(.067)	(.084)	(.037)
Capital, k_t	.068**	.081*	.099**	.100**
	(.025)	(.037)	(.036)	(.021)
IT labor, l_t^c	.026**	.010*	.043**	.026**
	(.009)	(.004)	(.012)	(.006)
IT capital, k_t^c	.027**	.035**	.038**	.041**
	(.009)	(.008)	(.009)	(.008)
Neighbor's IT labor, $l_{-i,t}^c$	–	–	–	$-.002$
				(.011)
Neighbor's IT capital, $k_{-i,t}^c$	–	–	–	$-.012$
				(.001)
ρ	.641**	.858**	.882**	.679**
	(.046)	(.038)	(.026)	(.043)
ComFac	.149	.010	.000	.334
No. of obs.	697	1,616	591	2,556
No. of hosp.	63	147	54	232

Note: NFP is not-for-profit and FP is for-profit. Standard errors are in parentheses. $^{*}: p < 0.05$, $^{**}: p < 0.01$.

share of total IT costs) are not observed in their data or the cost of unobserved organizational investments.

We perform several robustness checks for bias due to unobserved complementary inputs. First, organizational complements, such as works flow reorganization and changes in job design would likely lag IT capital investments, leading to vintage effects. Second, complementary organizational investments may play a bigger role for large IT investments. Finally, unobserved complements would likely lead to a correlation between IT investments and MFP. We find no evidence of vintage effects (see below) and no evidence that IT value differed for small or large investments.

We calculate the change in MFP over 1997–2007 using our parameter estimates. The weighted (by 2007 value-added) average percent change in hospital MFP over this period is 2.0% and the standard deviation is 18.2%.[35] There was virtually no change in the average MFP across hospitals, and there is little difference in the change in MFP across NFP and FP hospitals (approximately 4.5%). However, government hospitals saw a significant decline in MFP of 5.6%. We find no correlation between IT inputs and MFP.

These results further imply that the vast majority of the increase in hospital value-added over this period is directly tied to the expansion of hospitals' capital and labor inputs. These findings align with Cutler (2010) who contends that, unlike most other industries, the necessary forces are not in place to drive changes in organizational productivity in health care delivery.

□ **Organizational differences, network externalities, and vintage effects.** In this subsection we examine several, important ancillary questions that shed light on the underlying mechanisms through which health IT affects productivity. Specifically, we examine whether: (i) Does for-profit status affect the productivity of health IT? (ii) Does hospital size affect health IT productivity? (iii) Are there network effects from competing hospital adoption of health IT? (iv) Are there vintage or learning effects in health IT?

Table 3 presents production function estimates by hospital ownership structure.[36] Hospital ownership may play an important role in their organizational objectives and may influence

[35] Unweighted means and standard deviations yield similar conclusions.

[36] ACF parameter estimates for specifications discussed in this section are presented in the Appendix, Table A1. Differences in these estimates do not materially affect our conclusions.

TABLE 4 DPD Estimates By Bed Size, Time Frame, and Extent of IT Capital Investment

Variable	≤ 173 beds (1)	>173 beds (2)	Small IT Capital (3)	Large IT Capital (4)	1997–2001 (5)	2002–2007 (6)
Labor, l_t	.718**	.870**	.885**	.679**	.441*	.783**
	(.073)	(.049)	(.064)	(.065)	(.217)	(.046)
Capital, k_t	.140**	.084**	.089**	.151**	.256**	.142**
	(.034)	(.028)	(.029)	(.037)	(.085)	(.029)
IT labor, l_t^c	.023**	.013**	.016**	.022*	.005	.030**
	(.008)	(.06)	(.006)	(.009)	(.025)	(.008)
IT capital, k_t^c	.029**	.034**	.032*	.034**	.047	.046**
	(.009)	(.011)	(.015)	(.008)	(.044)	(.009)
ρ	.773**	.711**	.733**	.767**	.824**	.641**
	(.053)	(.047)	(.047)	(.054)	(.042)	(.046)
ComFac	.131	.042	.259	.006	.635	.145
No. of obs.	1,452	1,452	1,460	1,444	1,159	1,745
No. of hosp.	132	132	133	131	105	159

Note: Standard errors are in parentheses. Small (large) IT was defined as the lower (higher) 50% of IT capital/bed in the last observed year. * : $p < 0.05$, ** : $p < 0.01$.

investment behavior (Sloan, 2000; Horowitz and Nichols, 2009; David et al., 2011). Although we cannot directly incorporate these heterogeneous hospital preferences into our model, we can estimate the model dividing the sample according to ownership status. These results are reported in the first three columns of Table 3. Although the health IT parameter estimates differ across ownership structures, the standard errors are large enough that we cannot reject that the coefficients for NFP, FP, and government hospitals are equal. That being said, because FP hospitals invest significantly less in health IT capital, the implied marginal product is much higher than for other hospitals. These results combined with the evidence presented above suggest that FP hospitals invest differently in health IT.

Table 3 also presents our estimates of the impact of network effects from neighboring hospitals' health on IT productivity in column (4). Parameter estimates for $l^c_{-i,t}$ and $k^c_{-i,t}$, which measure the effect of neighbors' health IT inputs, are close to zero, statistically insignificant, and precisely estimated.[37] That is, we find no evidence of network externalities. This is not surprising. As discussed in Section 2, these technologies are not usually interoperable across hospitals and, in general, hospitals do not exchange medical record information with competing institutions. The policy implication is that network externalities from competitors' investments do not cause suboptimal levels of IT adoption.[38]

We also examine whether there is meaningful hospital-level heterogeneity in the impact of health IT on value-added. This heterogeneity may be related to hospital size or to the size of the hospital's IT investment. To explore this issue, we split the sample in half based on the number of staffed beds and the size of the IT investment and estimate parameters for each of these samples. Table 4, columns (1) and (2) presents the results from splitting the sample at the median sized hospital and columns (3) and (4) present these results for splitting the sample at the median change in IT capital between 1997–2008.[39] Parameter estimates indicate that there is virtually

[37] The qualitative implications of these estimates are robust to using different circumferences to define neighboring hospitals. In particular, we estimated the model using 10-, 20-, 30-, 40-, 50- mile radii and HSAs. In none of these specifications did competing hospitals' use of IT inputs significantly affect value-added. These results are presented in the Appendix, Table A4.

[38] It is possible that there are other sources of network externalities in hospital IT adoption. In particular, hospital adoption of EMRs may increase the value of physician group adoption of interoperable EMRs. Our data do not allow us to test for the presences of hospital-physician network externalities.

[39] We replicated the analysis in Table 4 using the ACF approach. Those results are presented in Table A2 in the Appendix and are not materially different from the estimates presented in Table 4.

no significant difference in health IT parameters across these four samples; however, there are differences in the other parameters. Although the coefficients are all significantly different from zero, the standard errors are large enough that the estimates may not distinguish modest differences in parameters across hospital categories.

Our data cover a significant span of time during which improvements in the productivity of health IT likely occurred.[40] Rapid innovation would lead us to underestimate the impact of future health IT investments. Therefore, we tested for vintage effects by examining whether the output elasticity of health IT increased over our study period. We divided the data into two samples based on the year of the observation. The samples periods are 1997–2001 and 2002–2007. Table 4, columns (5) and (6) presents production function parameter estimates for these two samples. Estimates suggest that health IT became more productive over time. The health IT labor parameter, in particular, is larger in the 2002–2007 period and significantly different from the 1997–2001 period parameter (which is close to zero). The IT capital parameter is also larger in the later period but the differences are not significant. Although parameters are larger in the later period, the economic implications of these differences are modest and do not materially affect our conclusions regarding the impact of health IT expansions on value-added. Alternative specifications allow the effects of IT inputs to change after adoption. Changes could capture either learning or innovation effects. These effects were small in magnitude and not significantly different from zero.

□ **Alternative specifications.** The Cobb-Douglas specification imposes strong functional assumptions on output elasticities and marginal productivity. We thus estimate a series of more flexible specifications, including a translog specification. These models incorporate interactions between IT inputs and other inputs as well as higher-order terms of IT inputs. These terms were incorporated into the models individually. These additional parameters were not statistically significant, and the overall model results were similar to those reported above. We also incorporated these changes simultaneously using a translog specification. The results suggest that the translog model is not a compelling specification here.[41] Most higher-order terms were statistically insignificant, and the parameters implied implausible marginal products (i.e., large negative gross marginal products of labor for all observations). Other studies of IT and productivity have had similar difficulties in employing more flexible specifications (Brynjolfsson and Hitt, 1996, 2003; Tambe and Hitt, 2012). Thus, we find little convincing evidence indicating that our results are driven by the Cobb-Douglas assumption or that health IT has a more complex (and perhaps more interesting) impact on value-added than implied by the Cobb-Douglas production function.

7. Conclusion

■ We study the effect of IT capital and labor on productivity. We employ a variety of identification strategies as hospitals' IT investments are both persistent and endogenous. Naive identification strategies underestimate the effect of IT on productivity, suggesting that IT investments are correlated with negative productivity shocks. These shocks may include unobserved quality or patient severity.

Hospitals' IT investments are highly productive at the margin. The median long-run net marginal products of IT inputs are \$1.04 for IT capital and \$0.73 for IT labor. We find that the value of increased IT inputs diminishes slowly and that inputs are complementary (consistent with the Cobb-Douglas constant elasticity of substitution assumption). Health IT's high marginal product suggests that widespread adoption may generate large productivity gains. Although the

[40] Discussions with industry experts point to meaningful improvements in the functionality of health IT over this period.

[41] The results are presented in Table A3 in the Appendix.

marginal benefits are high, IT represents a small share of total inputs and the absolute benefits are modest. Doubling IT capital inputs would increase total value-added by less than 2%.

These high-marginal products raise interesting questions about the efficiency of IT adoption. In equilibrium, hospitals should employ inputs until their long-run net marginal products are $0. An important limitation of our study is that we do not observe complementary organizational inputs such as training or work flow reorganization. Complementary input costs could lead us to overestimate the marginal products of IT inputs. Although unobserved complements certainly matter, we show any such bias is unlikely to be driven by complementarities related to hospital size or network externalities from nearby hospitals.

Our findings suggest that IT inputs are, at the margin, underutilized. Several mechanisms could lead to underinvestment in health IT. With a rapidly changing technology, there may be imperfect information or uncertainty regarding the costs and benefits of investment. Our long-run net marginal product estimates assume that the risk and uncertainty of IT investments are similar to those of a hospital's core business. This uncertainty may be important as Song et al. (2011) find that even sophisticated health care systems have made no attempt to calculate the return on IT investments and the empirical literature provides few insights into this question. Furthermore, hospitals (particularly not-for-profit institutions) often lack access to capital markets. The high-marginal products could also reflect shortages in skilled IT labor in the California market, either for hospitals or health IT vendors. Under these conditions, adoption subsidies would be welfare enhancing.

We also consider the possibility that health IT's value depends on network externalities. For example, neighboring hospitals' use of interoperable medical records systems could directly increase the value of health IT investments. Alternatively, provider and staff learning could lead to indirect network effects. We test this issue and find no evidence of network externalities from neighboring hospitals' IT investments. However, Dranove et al. (2012) find evidence consistent with network effects from EMR adoption and Miller and Tucker (2011) find that hospitals are strategic in their data sharing activities. Furthermore, California's strict privacy protection laws may prevent hospitals from sharing clinical data and realizing network externalities (Miller and Tucker, 2009). We also recognize that comprehensive electronic health records systems are rare (Jha et al., 2009) and the role of direct network effects may increase as formal information exchanges are fully implemented and more sophisticated IT systems are adopted by both physicians and hospitals.

Health IT utilization differs substantially by hospital ownership status. For-profit hospitals utilize 83% less IT capital than not-for-profit hospitals. For-profit institutions also utilize more IT labor per dollar of IT capital. We find that the marginal products of IT inputs are higher in for-profit institutions. Application level-data indicate that for-profit institutions lag their non-profit peers in the adoption of potentially quality-enhancing systems. These findings suggest that ownership structures affect hospitals' health IT adoption strategies. One important limitation of our study is that we do not directly observe quality and for numerous reasons the quality impact of health IT may not manifest in value-added. Although this should not bias our estimates of IT and value-added, we may underestimate the total welfare gains from health IT investments.

Appendix

The Appendix tables provide additional robustness tests describing results based on alternative identification strategies, parameter heterogeneity across hospital types, alternative specifications, and different market definitions.

TABLE A1 ACF Estimates By Ownership Type and Tests of the Presence of Network Effects

Variable	FP (1)	NFP (2)	Government (3)	Network Effects (4)
Labor, l_t	0.809**	0.780**	0.610**	0.796**
	(0.051)	(0.031)	(0.081)	(0.031)
Capital, k_t	0.139**	0.185**	0.201**	0.172**
	(0.033)	(0.037)	(0.042)	(0.022)
IT labor, l_t^c	0.007	0.006	0.025*	0.005
	(0.010)	(0.003)	(0.011)	(0.003)
IT capital, k_t^c	0.032*	0.038**	0.034**	0.036
	(0.013)	(0.005)	(0.010)	(0.006)
Neighbor's IT labor, $l_{-i,t}^c$				− 0.013**
				(0.005)
Neighbor's IT capital, $k_{-i,t}^c$				− 0.002
				(0.007)
No. of obs.	856	1,859	677	3,097
No. of hosp.	78	169	62	281

Note: NFP is not-for-profit and FP is for-profit. Standard errors are in parentheses. $^*: p < 0.05$, $^{**}: p < 0.01$.

TABLE A2 ACF Estimates By Bed Size and Time Frame

Variable	≤ 173 beds (1)	>173 beds (2)	Small IT Capital (3)	Large IT Capital (4)	1997–2001 (5)	2002–2007 (6)
Labor, l_t	.768**	.792**	.772**	.787**	.717**	.792**
	(.054)	(.030)	(.041)	(.137)	(.073)	(.048)
Capital, k_t	.172**	.175**	0.203**	.184**	.244**	.140**
	(.022)	(.029)	(.030)	(.034)	(.039)	(.037)
IT labor, l_t^c	.011*	.010*	.008	.011	− .0008	.012**
	(.005)	(.005)	(.007)	(.005)	(.006)	(.004)
IT capital, k_t^c	.035**	.025**	.021*	.036**	.028**	.036**
	(.007)	(.006)	(.006)	(.009)	(.006)	(.004)
No. of obs.	1,707	1,685	1,689	1,703	1,572	1,820
No. of hosp.	155	153	153	201	154	165

Note: Standard errors are in parentheses. $^*: p < 0.05$, $^{**}: p < 0.01$.

TABLE A3 DPD Estimates of a Second-Order Translog Production Function

Variable	Coefficients
Labor, l_t	$-.052$
	(.685)
Labor^2, l_t^2	.154**
	(.050)
Capital, k_t	1.076*
	(.459)
Capital^2, k_t^2	.092**
	(.031)
IT labor, l_t^c	.442**
	(.123)
IT labor^2, $l_{t^2}^c$	.000
	(.004)
IT capital, k_t^c	.072
	(.125)
IT capital^2, $k_{t^2}^c$	.014**
	(.004)
IT capital × IT labor, $k_t^c \times l_t^c$	.003
	(.007)
IT capital × capital, $k_t^c \times k_t$	$-.011$
	(.015)
IT capital × labor, $k_t^c \times l_t$	$-.016$
	(.016)
IT labor × capital, $l_t^c \times k_t$	$-.002$
	(.015)
IT labor × labor, $l_t^c \times l_t$	$-.023$
	(.016)
Capital × labor, $k_t \times l_t$	$-.227$**
	(.074)
ρ	.700**
	(0.043)
ComFac	0.542

Note: Standard errors are in parentheses. * : $p < 0.05$, ** : $p < 0.01$.

TABLE A4 DPD Estimates of the Network Effects Using Alternative Market Definitions

Variable	10 Miles	20 Miles	30 Miles	40 Miles	50 Miles	HSA
Labor, l_t	.899**	.829**	.830**	.807**	.767**	.876**
	(.035)	(.039)	(.037)	(.041)	(.038)	(.037)
capital, k_t	.089**	.127**	.100**	.128**	.147**	.071**
	(.024)	(.025)	(.021)	(.026)	(.026)	(.024)
IT labor, l_t^c	.014**	.025**	.026**	.028**	.022**	.012**
	(.006)	(.007)	(.006)	(.008)	(.007)	(.005)
IT capital, k_t^c	.043**	.037**	.041**	.035**	.042**	.023**
	(.008)	(.008)	(.008)	(.008)	(.008)	(.009)
Neighbor's IT labor, $l_{-i,t}^c$	$-.007$	$-.0004$	$-.002$	.002	.006	$-.005$
	(.008)	(.008)	(.011)	(.010)	(.011)	(.008)
Neighbor's IT capital, $k_{-i,t}^c$	$-.005$	.008	$-.012$	.008	.003	.007
	(.013)	(.013)	(.009)	(.007)	(.010)	(.008)
ρ	.658**	.637**	.679**	.645**	.662**	.602**
	(.043)	(.044)	(.043)	(.043)	(.042)	(.040)

Note: Standard errors are in parentheses. HSA is a Health Service Area ** : $p < 0.01$.

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