# Health Care Information Technology, Work Organization, and Nursing Home Performance

**Lorin M. Hitt and Prasanna Tambe***

**Abstract:** The authors investigate whether electronic medical record (EMR) systems are associated with higher levels of nursing home performance. Their difference-in-differences analysis is based on a survey of health care information technology (HIT) use in approximately 304 New York State nursing homes, combined with regulatory data from Center for Medicaid and Medicare Studies (CMS) Nursing Home Compare database and the New York State RHCF-4 financial reports. For nursing home owners, the authors find a positive effect of EMR-system implementation, on the order of 1% higher productivity, 3% greater efficiency, and about 2.7% higher cost. They also find that EMR systems amplify the returns to modern workplace organization. Facilities that are 1 standard deviation higher on a work-organization scale—composed of practices that encourage employee collaboration, decision making, suggestions, and problem solving—have no adverse cost impact of adoption of HIT, and adoption of HIT is associated with a productivity increase of 1.5% or more. They find no evidence of an impact on health care quality.



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The productivity of nursing homes is of considerable importance given the increasing demands that medical care is placing on federal and state budgets, and the aging of the U.S. population, which is expected to considerably increase the demand for nursing home services. New York

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State alone has more than 111,000 residents in nursing homes (about 7% of the national total) and spent nearly $21 billion in Medicaid disbursements on long-term care in 2008 (Moses 2011).

Health care information technology (HIT) has the potential to affect nursing home outcomes in a number of ways. In the broader health care sector, HIT has been linked to reduced costs, fewer medical errors, and improved patient care, and these benefits could also apply to nursing homes. These benefits, however, are unlikely to be realized in equal measure across homes. Prior literature has demonstrated that new information technologies (ITs) are often most effective in organizations with workplace practices that empower employees to use their skills to solve problems. In this article, we investigate the effects of HIT implementation in nursing homes on productivity, costs, efficiency, and quality, and we test the hypothesis that returns to HIT will be greater in homes with work organization that encourages front-line workers to collaborate and empowers them to directly make patient care decisions.

The key new data source we used for the analysis is a survey administered through the Cornell Survey Research Institute to all New York nursing homes with at least 60 beds. Of the 538 nursing homes in this category, we received survey responses from 304, for a response rate of about 57% of all large, privately operated nursing homes in New York. The survey included questions about the HIT implementation date as well as a series of questions drawn from the prior literature that characterize the work practices used at each nursing home. These data were supplemented using public data sources on the financial performance, costs, and health outcomes of nursing homes. Because we have the HIT implementation date and a seven-year panel of performance, costs, and efficiency data, we are able to perform a difference-in-differences analysis, which compares the performance of nursing homes before and after HIT implementation.

The article makes two contributions. First, our article contributes to the literature on complementarities between IT investment and work organization. Much of the prior work in this area focused on manufacturing. In health care settings, researchers have argued that work organization merits separate study because high-performance work practices facilitate the effective processing of equivocal information (such as patient health information gathered through visual examination) and improve relational coordination among health care workers. These studies linked the use of these work practices to better health care quality but did not consider managerial incentives to adopt these practices or how the diffusion of HIT systems might affect these incentives. To the extent that new technologies raise financial incentives to adopt these work practices, they can offset the costs of these practices, potentially improving patient outcomes. But, because patient information that is subject to interpretation may be difficult to codify and store in electronic systems, whether HIT systems raise or lower the value of work practices that facilitate the offline processing of patient information is uncertain.

Second, although a literature on HIT has been rapidly emerging, this is some of the first work to analyze how HIT affects nursing home performance. Because long-term care facilities account for significant health care spending and because the organization of work in long-term care facilities may differ substantially from that in hospitals, this setting merits separate consideration. Moreover, most empirical work on IT and performance has focused on top-line revenue, but health care has a broader range of stakeholders and policy-relevant metrics to consider. An analysis of how the benefits of HIT in nursing homes might be distributed between increased productivity, which represents a transfer, and greater efficiency, which suggests welfare gains, is important for informing policy related to the federal funding of HIT adoption in long-term care facilities.

## Prior Literature and the Empirical Setting

### Relevant Literature

*HIT and Nursing Home Performance*

Previous work on nursing home performance has considered the determinants of nursing home quality or costs with special emphasis on market characteristics such as competition (Gertler and Waldman 1992; Grabowski and Hirth 2003), organizational variables such as for-profit status (e.g., Arling, Nordquist, and Capitman 1987; Nyman and Bricker 1989; Fizel and Nunnikoven 1992; Spector, Selden, and Cohen 1998; Chou 2002) or chain membership (e.g., Fizel and Nunnikoven 1993; Banazak-Holl et al. 2002), organizational workflow and culture (Harrison, Koppel, and Bar-Lev 2007; Koppel, Wetterneck, Telles, and Karsh 2008), location (typically urban compared with rural, as in Spector et al. 1998), and policy variables such as a shift to prospective payment systems (Sexton, Leiken, and Sleeper 1989). In general, competition, for-profit status, and chain membership are associated with greater productivity or efficiency.

But this work did not address how the use of any type of HIT affects economic outcomes in long-term care. Prior work on HIT in long-term care settings focused on resident outcomes, such as adverse drug events or the prevalence of pressure ulcers (Judge et al. 2006; Gurwitz et al. 2008; Field et al. 2009; Milne et al. 2009; Lapane et al. 2011; Pillemer et al. 2012). HIT systems that enable the capture, processing and retrieval of resident medical records are believed to enable nursing homes to better manage the care process, improve the documentation of resident care, and free up time spent by direct-care staff on documentation and coordination to provide more substantive resident contact, potentially improving the quality of life of residents. The automation of the medication process is believed to reduce medication costs through eliminating waste and duplication, decreasing medication errors, and providing decision support to allow physicians to make better medication choices (fewer medications and/or ones lower in cost).[2] Other features of HIT systems in nursing homes enable off-site health care workers to obtain the information necessary to better support care. Finally, more accurate data capture on residents' health conditions and treatment may facilitate improved billing for services, yielding greater revenue. Electronic medical record (EMR) systems may also increase revenue if they allow facilities to attract private-pay and Medicare patients who receive higher reimbursement rates through greater service levels or perceived quality of care.

In the broader health care sector, case studies have linked HIT to reduced costs, reduced medical errors, and improved patient care. In addition, a limited number of large-sample statistical studies have also shown modest, positive benefits from HIT investments (see a brief review in Housman, Hitt, Elo, and Beard 2009). Firms at the leading edge of HIT investment may have productivity around 1 to 3% greater than other firms that have made less substantial HIT investments.

*HIT and Work Organization*

Generally, the prior literature has argued that organizations with work practices that enable information sharing and decentralized decision making may be better at using information in production. Employees in these organizations are better able to apply their skills to problems that arise at work. In health care, prior work has shown that workplaces that facilitate information sharing and point-of-care decision making are associated with superior patient outcomes (West et al. 2002; Preuss 2003; Gittell, Seidner, and Wimbush 2010).

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[2] For a vendor's perspective on the benefits of HIT, see "SigmaCare/eHealthSolutions (2007**)**

Our study builds on studies in this literature as well as on work that provides evidence that collaboration, problem solving, and decision making by front-line workers complement technological investment (MacDuffie 1995; Batt 1999; Bresnahan, Brynjolfsson, and Hitt 2002; Hunter and Lafkas 2003; Litwin 2011 is a health care example). A relevant finding is that firms that use decentralized decision making receive greater benefits for each dollar of IT investment (Bresnahan, Brynjolfsson, and Hitt, 2002; Tambe, Hitt, and Brynjolfsson 2012; for a review, see Melville and Kraemer 2003). Most prior IT value studies have used a production-function framework in which output is regressed on some combination of inputs (Brynjolfsson and Hitt 2003; Tambe and Hitt 2012). This approach is perhaps easier to interpret than cost functions or efficiency scores, but it has the drawback that it can handle only a single type of output at a time, so studies that use this approach are limited to examining overall revenue as the primary output.

This existing literature, however, has not assessed how HIT affects the role of work practices in health care delivery. EMR systems transform how patient information is collected, stored, distributed, and accessed. Automating medical documentation increases the time health care professionals spend with nursing home residents, allowing greater time for assessment. HIT systems can also consolidate medical information, improving the efficiency with which information can be delivered to workers directly involved with patient care. In either case, productivity and efficiency gains are most likely to be realized if front-line workers are empowered to use this time and information to improve the quality of care for residents.

Nevertheless, health information is complex and capturing it in an electronic format may prove difficult. Preuss (2003) and Gitell et al. (2010) placed the costs of information exchange at the center of why high-performance work practices improve health care quality outcomes. Therefore, we do not know whether EMR systems, by enabling more efficient information exchange, substitute for the offline information benefits of high-performance work practices identified in prior work on health care or whether, by consolidating medical information in one location, they increase the returns to using practices that enable front-line workers to combine this information with more complex point-of-care information and make informed decisions. In the latter case, HIT systems are likely to amplify the returns to the types of work practices described in the prior literature on high-performance systems and health care.

**Setting**

A typical nursing home in New York State has about 200 beds and provides care for a stable long-term population of elderly residents (who can stay many years), along with a transient population of rehabilitation patients (who may stay for as long as several months). Care generally involves providing housing, food, and daily activities for the residents, along with any required therapy, administration of medications, and medical care. Nursing homes are staffed principally with certified nurses aides (CNAs), who are directly responsible for resident care. The CNAs are typically supervised by nurses (either licensed practical nurses [LPNs] or registered nurses [RNs]) who, in turn, are supervised by the nursing home manager. Most nursing homes also contract with doctors and other specialists, such as dentists and psychologists, for more complex health care services.

Each resident has a care plan that is implemented by the CNAs, and the completion of these activities is recorded in their medical charts and monitored by the nursing staff. A major part of daily operations is assigning and managing the CNA workload and recording data about the residents and the implementation of their care plans. These two activities—workflow management and electronic medical records—are what nursing home HIT systems principally provide. These systems may also automate administrating medications, ordering laboratory tests, filling prescriptions, and coordinating with outside providers (e.g., contracted doctors), although considerable variation is present in the use of these features.

The financial structure of nursing homes is complex. Homes are either privately owned (proprietary), operated by nonprofit institutions (often with religious affiliations), or government run. In total, between 600 and 700 nursing homes operate in New York in any given year. Most nursing home care is paid for through Medicaid (a combined federal and state program for providing care to low-income elderly individuals), with a small portion of private pay or individual insurance, and Medicare for rehabilitation patients. For the homes we consider, the payer mix is about 73% Medicaid, 12% Medicare, and the rest private pay or private insurance. Most payment is based on a prospective payment system, which bases reimbursement on a combination of prior year costs and the resident's health condition. The standard unit of payment is a resident-day, and the payment per unit can vary from about $200 to $500, depending on the condition of the resident and on the payer.

Capital investment in nursing homes is strictly regulated through a certificate-of-need process whereby homes must apply to the state for permission to make capital investments. In practice, this means that capital investment is infrequent, and most facilities operate at a very high utilization (85%-plus occupancy). Although reimbursement is based on costs, lags between cost savings and reimbursement changes provide a short-term incentive to increase productivity. In the longer run, the incentive to adopt new technologies is more likely to be found in the retention of higher-paying residents.

## Data and Measures

### EMR Adoption and Work Organization

For our analysis, we construct a data set consisting of a) survey data collected from nursing homes in 2013, b) longitudinal data on home financial variables from 2004 to 2011 taken from New York State Residential Health Care Facilities Cost Reports (RHCF)-4 filings, and c) quality information from the Center for Medicaid and Medicare Studies (CMS) Nursing Home Compare database. We eliminate any facilities that spent less than 20% of expenses on staff because these facilities (only about 5% of the sample) operate principally with contract labor and their financial statements are very different from the other homes.

The primary unique data source for this analysis is a survey conducted in mid-2013 on HIT use and work practices in New York State nursing homes. From an initial population of approximately 600 homes, we removed homes that were government operated, those that had fewer than 60 total nursing home beds, and those that had participated in the demonstration project. We contacted nursing home owners or administrators identified through the homes' regulatory filings (RHCF-4) for either an interview directly or a referral to an informed respondent. The survey was conducted by the Cornell University Survey Research Institute (SRI) and was pretested on demonstration project homes before being deployed in the field. The survey was conducted on an initial population of 538 homes, and we received responses from 304.[3] Although our data collection is retrospective, which raises issues of accuracy because of imperfect recall, most of our respondents were in low-turnover management roles (e.g., nurse manager) with active involvement in facility operations.

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[3] We did a two-sample *t*-test comparing facilities in the sample with those meeting the test criteria and not in the sample (at least, 60 beds and not government operated) for all the measures reported in Table 1. Facilities in the survey sample are less likely to be in the New York metro area (24% compared to 33%) and have a slightly lower fraction of Medicare residents (2.5% less). None of the other measures showed a difference at $p < 0.05$.

The survey focused on the HIT implementation date, the features used (EMR system, medication administration, and remote access), and the extent of staff use. In addition, we included several questions that had proven helpful in prior work in discriminating nursing homes by their work practices (Avgar and Lipsky 2010; Lipsky and Avgar 2011). The specific questions in the survey asked respondents to evaluate on a 5-point scale whether they agreed or disagreed with the statement that their homes had adopted the following elements of workplace design:

<nl>1. Collaboration (in-unit): Employees in a resident care unit share information freely with one another.

2. Collaboration (cross-unit): Workers freely share information with employees in other resident care units.

3. Suggestions: Unit supervisors seek and act on ideas and suggestions made by the direct-care staff.

4. Problem solving: When a problem arises in a resident unit, the staff members generally try to solve it as a group.

5. Discretion: Employees are given the freedom to make important resident-care decisions

Our measure of work organization is the standardized sum of the standardized values of these five measures. The individual components of this measure overlap closely with measures used in the prior literature on complementarities between IT and work organization (Batt 1999, 2002; Bresnahan et al. 2002; Hunter and Lafkas 2003; Preuss 2003; Litwin 2011).

The most critical question in the survey was the date, if any, of EMR adoption. Because EMR systems are generally the first HIT technology adopted, this represented the first HIT adoption date. For the facilities we observed in this and prior work, implementation is typically done across the facility over the course of one to three months. Although HIT systems can provide other capabilities beyond EMRs, our preliminary analysis suggested that we would be unable to distinguish these effects separate from EMR use, which is our focus. In our data, 63% of facilities adopted EMR systems by the end of 2013, with the earliest adoption date being 2005.

**Financial Data**

Our primary source for financial and operating data is the RHCF-4. These data are generated by the Medicaid rate-setting process and have been extensively used in prior research. We use the 2004 to 2011 data for our estimates (the 2004 cutoff was chosen because this was one year prior to the earliest adoption date). These data include revenues, resident mix (resident-days and revenues by payer: Medicaid, Medicare, or private), staffing by role, for-profit status, location, presence of a union, costs (labor, materials, and purchased services), number of beds (bed size), and services provided. The staffing data are divided into RNs, LPNs, CNAs, administrators and managers, other medical staff, and clerical and administrative staff.

Generally, the values of the RHCF-4 data were taken directly, although a small percentage of coding error is present in the data. By looking across years, we were able to correct some errors (e.g., incorrect home identifiers and missing bed size). Outliers (the top and bottom 1% of staffing and financial measures) were examined and eliminated if the value could not be verified. Data elimination was done on a casewise basis, but to keep consistent samples between the productivity and cost-function analyses, missing data on some constructs caused us to remove that home observation from all analyses.

**Quality Measures**

Nursing homes are subject to annual inspections in which the facility and resident conditions are evaluated by government inspectors. A summary of inspection results (survey) is made publicly available at a facility level in the CMS Nursing Home Compare database. Nursing Home Compare (NHC) is based on two other sources: the CMS Online Survey, Certification and Reporting (OSCAR) database, and the CMS Nursing Home Minimum Data Set (MDS) database. The Nursing Home Compare data contain three types of data: quality measures (QMs), which are a summary of the health conditions of individual residents (18 measures total) and are derived from the MDS; complaints received (individually listed and categorized by severity); and facility deficiencies identified by the survey team during site visits (also individually listed and categorized by severity), which are derived from OSCAR data. We aggregated the measures for quality, complaints, and deficiencies to form three scales, using methods similar to those use by CMS to construct aggregate quality measures in its star-rating system (for this methodology, see Center for Medicare and Medicaid Studies 2010). The aggregate measures are created by assigning points to each level of a particular measure, with more points assigned to more severe or important conditions. The principal measures used in the study are summarized in Table 1 for 2009, which is halfway between the beginning and end of our panel.[4]

## Methods

**Before and After Comparisons**

[4] Our primary sample includes the facilities for which we have complete data, including a response on the survey, costs data from RHCF-4, and quality information.

Existing studies on nursing home performance used a variety of methods, including economic cost functions (Arling et al. 1987; Gertler and Waldman 1992; Mukamel and Spector 2000) and data envelopment analysis (DEA) frontier methods (e.g., Nyman and Bricker 1989) that seek to identify efficient facilities (output per input cost). Some studies have also used stochastic production frontiers (Vitaliano and Toren 1994), a hybrid of cost functions and DEA. An emerging literature on HIT in hospitals has relied on similar methods (typically cost functions, with some DEA) to link use of various HIT systems to performance. Much of this earlier work was in the form of case studies and anecdotes (e.g., see GAO 2003 for a summary); however, a few studies estimated the impact of HIT on outcomes using large data samples and more structured economic models (Borzekowski 2002; Housman et al. 2009; for cost-function studies, Atkinson and Cockerill 2006; for DEA, Menon, Lee, and Eldenberg 2000). One recent study used an extension of the traditional productivity framework (Lee, McCullough, and Town 2013).

To examine whether the implementation of EMR systems had a substantial effect on various measures of nursing home operations, we conduct a difference-in-differences analysis of whether operating or performance measures changed more in nursing homes that implemented EMR systems than those that did not over equivalent time periods, controlling for possible differences in the population of eventual adopters from the population of nonadopters. The general form of the estimating equation is, for each home ($h$) in each year ($t$):

$$(1) \quad \text{PerformanceMeasure}_{h,t} = \alpha + \beta_{\text{EMR}}\text{UseEMR}_{h} + \beta_{\text{AfterEMR}}\text{AfterEMR}_{h,t} + \text{year}(t) + \text{other controls} + \varepsilon_{h,t}$$

The variable UseEMR takes the value 1 if the home ever used an EMR system and 0 otherwise. This variable controls for pre-existing differences between implementers and nonimplementers of EMR. The variable AfterEMR takes the value 1 for the year the EMR system was implemented and all subsequent years, and 0 otherwise. In contrast to hospitals, many nursing homes have minimal IT except for personal productivity applications. Therefore, a binary adopter/nonadopter measure reasonably captures nursing homes' EMR investment, as opposed to a continuous investment metric or the number of applications deployed, which has been used in the HIT literature related to hospitals.[5] AfterEMR is the primary variable of interest because it has an interpretation as the marginal effect of EMR implementation in this framework. Whether this can be interpreted as causal depends on whether common factors can be identified that coincide with EMR implementation time and affect performance for only the period after implementation. We experimented with considering time since adoption or defining post-adoption as the year following adoption; however, neither of these appeared to yield improvements in the analysis.

To test the complementary effects of work organization on EMR use, we augment the model in Equation (1) with work-organization (WO) measures. The full model is shown in Equation (1a).

$$\text{(1a)}\quad \text{PerformanceMeasure}_{h,t} = \alpha + \beta_{\text{EMR}}\text{UseEMR}_{h} + \beta_{\text{WO}}\text{WO}_{h} + \beta_{\text{AfterEMR}}\text{AfterEMR}_{h,t} + \beta_{\text{WO*EMR}}(\text{WO*UseEMR}_{\text{h}}) + \beta_{\text{WO*AfterEMR}}(\text{WO*AfterEMR}_{\text{h},t}) + \text{year}(t) + \text{other controls} + \varepsilon_{h,t}$$

Under the conditions described here, a positive and significant estimate of the coefficient on (WO*AfterEMR) provides causal evidence of the argument that EMR systems drive higher

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5 Prior to the deployment of the EMR systems in our sample of nursing homes, most homes had minimal IT investment and what was there was limited to personal productivity and single-user applications (e.g., the software that prepares the reports for the MDS or nursing home cost reports), and most of these were used exclusively by managers and the senior (supervisory) nursing staff. When the EMR system was implemented, it was typically the first enterprise application in these facilities. In contrast, almost all hospitals already had an existing IT infrastructure and many administrative applications in place prior to the current wave of HIT investment.

performance levels in nursing homes that have higher measures of work organization, as measured on our scale.

All regressions here and in subsequent models (unless otherwise noted) use this difference-in-differences approach and include controls for year to account for shifts in the performance measure attributable to external economic conditions. All analyses either include nursing home fixed effects or include additional controls for differences among facilities unrelated to EMR use. These are discussed next.

We include quality measures because, plausibly, higher quality has an influence on costs or other performance measures. We include the three indices for quality computed from NHC (Quality score, Deficiency score, and Complaint score). Almost all prior work in nursing home performance contained some controls for quality.

The RHCF-4 survey lists 20 services that can be performed in nursing homes or contracted out, so we control for the number of services performed (Services). More services are likely to be associated with greater revenue and greater cost, with the cost effect potentially larger because of a greater complexity of management. The typical nursing home in the sample performs 11 of the 20 services listed on RHCF. The Services count is related to the scope of the home, but most services are performed by outside contractors, not CNAs.

We control for resident composition because it directly influences revenue through payment and may indirectly represent other aspects of the home because nursing homes aggressively compete for private-pay residents but not for Medicaid residents. The resident composition variables are %Medicare, %Medicaid, and %Private (we drop the variable %Private because that is entirely determined by the other two given). In our sample, about 15% of residents are private pay and 74% are Medicaid, as measured in resident-days. Most prior studies included controls for resident composition.

Prior research has shown that for-profit facilities are more productive than not-for-profit facilities (e.g., see Arling et al. 1987), so we include a binary variable For-profit, representing for-profit status. About half of all facilities in our survey are for-profit. This variable appeared in essentially all prior nursing home studies, and the study of this specific variable has been the focus of much of the prior literature.

We include a control for presence in the New York metropolitan area (NYMetro) because prior work controlled for location and found that an urban location has an influence on costs and reimbursement (e.g., Nyman and Bricker 1989), and is also associated with the presence of a union (Unionization). Prior work was mixed on the typical signs of these variables. About 60% of the full sample is unionized and 30% is in the New York metropolitan area.

We use the logarithm of number of beds (log(Capacity)) as a control for scale. This variable also serves as a proxy for capital stock in later analyses. Generally, under the certificate-of-need regulation, which restricts capital investment, we expect to find increasing returns to scale,[6] so we expect this variable to be positively associated with performance. The average facility bed size is about 170.

Finally, we use an index of competition proposed by Gertler and Waldman (1992), [7] which is based on the insight that nursing homes aggressively compete for private-pay residents but that this degree of competition depends on the number of other homes in the same geographical region (in our case, the county). For each county, we compute the share of private-

[6] The sum of the production function coefficients estimated later in our analysis is approximately 1.02, which suggests slightly increasing returns to scale, although these are not significantly different than 1.

[7] This measure is the sum of squared market shares within a county for private-pay residents. A higher value of this measure indicates less competition because the market is less concentrated. Prior work has suggested that competition for private-pay residents is a substantial driver of costs and quality (Gertler and Waldman 1992).

pay residents each nursing home has (from RHCF) and then compute a Herfindahl index as the sum of squared market shares. The index ranges from 0 to 1, with 1 representing a monopoly over a geographical region and 0 representing the presence of an infinite number of facilities, each with a very small market share. Overall, most of New York State is competitive, with a concentration index averaging less than 0.07.

These variables represent the majority of study variables considered in prior research, but some variables were deliberately omitted. We do not consider whether the nursing home is part of a chain because New York state law discourages the ownership of multiple nursing homes by the same legal entity and chains are technically not allowed. We do not control for the difference between intermediate-care and skilled-care residents because this distinction was not used in New York at the time of our study. Unfortunately, we do not have controls for case mix[8] because these data are not available in the RHCF or NHC data sets; however, as proxies we can use some combination of the other variables (the resident-composition variables and Quality score). Most of the other constructs that appeared in prior research but that we do not include were idiosyncratic to the specific data sets or are subsumed under our other measures.[9]

## Productivity

Much of the extant literature on IT productivity relied on methods from economic production theory (e.g., Brynjolfsson and Hitt 2003). The simplest of these is production function analysis, which posits a relationship between the output that a facility produces and the inputs it consumes. In this case, we consider the output to be either revenue or value-added (revenue

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[8] Case mix is often computed using restricted identifiable data direct from the MDS. We do not have these data for this study.

[9] We thank Sheldon Schecter and members of the Quality Care Oversight Committee (Martin Scheinman, Jay Sackman, and William Pascocello) for assistance in understanding business practices, regulation, and financial reporting in New York nursing homes.

minus the cost of purchased materials), and we consider the inputs to be labor (staff), physical capital (proxied by Bed size), and other expenses (materials and purchased services). A number of different relationships can be assumed that connect the outputs to inputs, but the simplest and most commonly used is the Cobb–Douglas production function, which assumes constant elasticities of substitution. We use this form because it is easy to interpret, has been used extensively in the literature, and provides a first-order approximation to any arbitrary production function. The estimating equation takes the form:

(2) $\log(\mathrm{VA}_{h,t}) = \alpha_0 + \beta_{\mathrm{Capital}}\log(\mathrm{Capital}_{h,t}) + \beta_{Labor}log(Labor_{h,t}) + \beta_{\mathrm{Expense}}\log(\mathrm{Expenses}_{h,t}) + \mathrm{year}(t) + \mathrm{controls}(h,t) + \varepsilon_{h,t}$

In Equation (2), the dependent variable is value-added (VA). The coefficients (β) represent the percentage change in output per percentage change in input quantity, and these are theoretically expected to be close to the ratio of inputs costs to output costs. In panel data (repeated observations of the same unit over time), binary variables are included for each year (*t*) to control for the effects of inflation, prices, and different economic conditions in each year. We also include measures that account for how the facilities (*h*) might differ in their ability to convert inputs into outputs, as described earlier: Quality score, Unionization, location in the New York metropolitan areas, resident mix, number of Services, for-profit status, and competition (bed size is not considered a control because it serves as the proxy for capital).

After including the measures for EMR-system adoption, we have the following estimating equation:

(3) $\log(VA_{h,t}) = \alpha_0 + \beta_{EMR}UseEMR_h + \beta_{AfterEMR}AfterEMR_{h,t} + \beta_{Capital}\log(BedSize_{h,t}) + \beta_{Labor}\log(Labor_{h,t}) + \beta_{Expense}\log(Expenses_{h,t}) + year(t) + controls(h,t) + \varepsilon_{h,t}$

This equation can also be augmented, as in Equation (1a), to test how complementarities between EMR systems and work organization affect productivity.

**Cost Functions**

Although production functions are common in the IT-productivity literature, they are less common in health care studies because they are limited to considering only a single output. In general, health care facilities provide a variety of outputs, such as serving patients or residents with different types of care needs. In addition, cost functions may be more appropriate when the quantity of output is largely fixed (e.g., capacity is fixed and capacity utilization is practically 100%) and cost minimization is an important managerial goal driving performance. Multi-output production has been modeled in two standard ways in nursing homes: cost functions and efficiency analysis.

The cost-function approach uses the same underlying economics as production functions, although the simple Cobb–Douglas form is no longer appropriate because it does not allow for sufficiently rich relationships between input quantities and input costs.[10] Therefore, we estimate a transcendental logarithmic (translog) cost function with two variable inputs (Labor and Expenses), one fixed input (Capital, proxied by Bed size), and three outputs (Medicare resident-days, Medicaid resident-days, and Private-pay resident-days). We include the same control variables as before except for the resident proportion measures, which are already subsumed in

[10] See Varian (1992) for a textbook discussion of the theory underlying production economics and Berndt (1991) for a discussion of the practice of estimating cost functions.

the outputs. The translog cost function contains first-order (linear), squared, and interaction terms between all inputs and outputs.

In cost functions, variable inputs are represented by their prices, which are computed as the cost of the inputs divided by the number of input units (for labor, the input units are full-time employment [FTE] employees; for expenses, they are resident-days). For fixed inputs, these are introduced in levels so our measure of capital is bed size. Outputs in cost functions are typically measured in physical units, in this case, the resident-days of each type of resident. The primary dependent variable is total variable costs, which is equal to the labor, materials, and purchased services costs (capital costs such as depreciation and nonoperating expense are excluded). The resulting estimating equation is thus:

(4)

$$logC = \beta_0 + \beta_{EMR}UseEMR + \beta_{AfterEMR}AfterEMR + \sum_{i\in\{Z\}} \beta_i X_i + \sum_{i\in\{Z\}} \sum_{j\in\{Z\}} \beta_{ij} X_{ij} + year(t) + controls(h,t) + \varepsilon$$

where *Z* is the set of inputs prices for variable inputs (price of labor and price of materials), fixed inputs (bed size), and output quantities (Medicare residents, Medicaid residents, and private-pay residents). We have suppressed the subscripts for time (*t*) and facility (*h*) on all variables and the residual. We estimate the cost-function equation described earlier both individually and as a simultaneous system with the labor demand equation as described in Berndt (1991). Because the results did not materially differ, we report only the single equation estimates. We did not impose any additional restrictions (e.g., convexity or monotonicity) on the structure of the function. Our results use a general specification that is similar to prior cost-function studies (Gertler and

Waldman 1992; McKay 1998), but they differ by disaggregating the output into three components, explicitly controlling for nursing home quality, and capturing labor as a single variable. The variable set was chosen as a reasonable trade-off between the complexity of the specification (the number of estimates is proportional to the square of the number of inputs and outputs) and capturing the essential features of the setting. Finally, we also augment it, as in Equation (1a), to test how complementarities between work organization and EMR systems affect costs.

**Efficiency Analysis**

A number of nursing home productivity studies have used DEA methods to analyze efficiency. Essentially, the procedure attempts to find the homes that are efficient in the sense that they produce the maximum amount of some combination of outputs given the quantity of inputs used. Each home then receives an efficiency score, which is the distance from this frontier. Efficiency scores range from 0 to 1, with 1 being fully efficient.

DEA analysis proceeds in two steps. First, efficiency scores are calculated for each facility in each year given a set of inputs and outputs. Second, regression analysis is used to examine how efficiency scores vary with variables of interest such as EMR-system adoption, For-profit status, location, Service breadth, and Unionization (the quality and output mix in this analysis can be handled with outputs). A critical trade-off required for DEA analysis is choosing an appropriate set of inputs and outputs that capture the richness of the production process while not having so many variables that homes cannot be compared to each other directly. With too many outputs and inputs, all homes appear on the efficient frontier because no two homes have exactly the same input–output composition. After some experimentation, we settled on a DEA model with four outputs: Medicare resident-days, Medicaid resident-days, and Private-pay resident-days (three outputs) and the quality measures score, Quality score (one additional output). For inputs, we include staff and expenses: the number of FTEs for nurses (RNs and LPNs), CNAs, and all other staff, along with the total nonlabor expense (a total of four inputs).

We estimated the DEA scores for each nursing home in each year from 2004 to 2011 using the input-oriented variable returns-to-scale DEA model (Banker, Charnes, and Cooper 1984). The variable returns-to-scale model was chosen because the productivity analysis suggested that the data do not show constant returns to scale, and we chose an input-oriented approach because capacity is not really under the control of the nursing home managers. The actual estimates were performed using DEAP (Coelli 2011).

We then estimated models of the form:

(5) $$EfficiencyScore_{h,t} = \alpha_0 + \beta_{EMR} UseEMR_h + \beta_{AfterEMR} AfterEMR_{h,t} + year(t) + other\ controls + \varepsilon_{h,t}$$

The controls in this regression are the same as before (omitting quality and resident mix, which are already part of the output set). Estimates were made using ordinary least squares (OLS) with Huber–White robust standard errors. We also report standard errors calculated using 50 samples of bootstrap estimation; some authors have argued that bootstrap errors are more reliable because the DEA procedure induces statistical dependence among efficiency scores in complex ways. No panel data equivalent of this approach exist, however, which could lead to the standard errors being understated by repeat sampling; therefore, significance levels must be interpreted conservatively.

**Quality Outcomes**

For our final tests, we examine how HIT implementation affects a number of nursing home quality outcomes, including indicators that have been considered in prior work (Judge et al. 2006; Gurwitz et al. 2008; Field et al. 2009; Milne et al. 2009; Lapane et al. 2011; Pillemer et al. 2012). We conduct these analyses because the operational improvements previously discussed may be associated with an erosion in quality of care. We test the effects of EMR-system implementation on a number of outcome variables, including those for staffing levels, quality indicators, and resident mix, using the specification described in Equation (1), where each of the different home outcomes is the dependent variable in the difference-in-differences analysis.

## Analysis

The summary statistics for our key measures are shown in Table 1, column (1). In columns (2) and (3), we report the results of a fixed-effects differences-in-differences analysis comparing the values of each measure for EMR adopters and nonadopters (essentially estimating Equation (1)). In general, little difference can be seen in most measures post-adoption compared to pre-adoption. The only notable exceptions are that gross margins are somewhat higher (about 2%), and overall average revenue per bed-day is higher by about $4.86 (also corresponding to about a 2% increase). This may be, in part, attributable to a slight increase in the proportion of Medicare residents and private-pay residents, for whom the reimbursement rate is higher. Also, employment expenses and total employment are slightly lower (by 1 to 2%), also potentially contributing to the increased margin. We also tested whether our sample differs from the survey population; we found no significant or material differences on any measure reported in Table 1 except for a slightly lower proportion of facilities in metropolitan New York (24% compared to

33%), and a slightly lower proportion of Medicare residents (about 1.5% less than the nonrespondent population).

## Productivity and Cost Functions

The primary results from the baseline value-added production function analysis are shown in Table 2, column (1). The comparable specification with the added EMR-adoption variables appears in column (2). These regressions contain the full set of controls described earlier and use OLS regression with Huber–White clustered standard errors to control for repeated observations of the same facility over time. In the latter specification, the implementation of EMR systems is not associated with a statistically significant productivity increase.

The coefficients on the other production inputs and control variables are generally as would be expected. The output elasticities of labor, expenses, and purchased services are about equal to their factor shares (the ratio of the input quantity to output quantity), consistent with the economic theory that these factors should earn normal rates of return. In addition, we find that for-profit nursing homes are about 1.7 to 2.6% more productive, consistent with prior work. Here and throughout, we use the approximation that the coefficient can be interpreted a percentage change. These percentage changes are increases in the annual output per unit input that persist over the relevant period (either the entire sample, or the post-adoption period, depending on the measure). Homes in New York City are about 2.5% more productive (possibly because of higher relative reimbursement rates after controlling for cost drivers). Of the quality measures, resident health quality is not significant, but firms with fewer complaints or deficiencies are slightly more productive. Most of the other control variables are not consistently significant, except the

Medicare percentage, which is consistent with higher reimbursement rates for Medicare residents.

To estimate the effect of IT-complementary workplace organization, we add in Table 2, column(3) additional variables for the use of work organization (WO) as well as their interactions with the use of EMRs and the post-implementation period of EMR-system use (UseEMR*WO and AfterEMR*WO). The point estimate of the primary variable of interest (AfterEMR*WO) in the base specification is 1.5% (significant at $p < 0.05$), suggesting that firms that are one standard deviation higher on the WO measure had a 1.5% productivity gain after EMR-system adoption.

We consider a number of other variants of the base specification, including using panel models with random effects (column (4)), fixed effects (column (5)), and robust (quantile) regression (column (6)) using value-added as the dependent variable. Random effects explicitly allow for individual nursing home effects (those addressed by Huber–White standard errors) and are theoretically more efficient if no other specification issues exist, but they often perform poorly in real data. Fixed effects control for all time-invariant characteristics of the facilities. Quantile regression is similar to OLS but is less sensitive to outliers. All return roughly similar results, with a 1.5 to 1.9% positive contribution (significantly different from 0 at $p < 0.05$ or better) from EMR-system adoption in nursing homes that use IT-complementary work organization. We also conducted two additional sets of robustness tests:  from 1) regressions comparing pre- and post-EMR-adoption performance only in homes that adopted EMR systems and 2) regressions in which the EMR use measures are lagged. The results from these tests are very similar to the main results reported in Table 2.[12]

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[12] Results available upon request.

Altogether, these results suggest a positive impact of EMR adoption across the sample. Because some estimates place the long-run annual operating costs of an EMR system at about 0.5% of total facility costs (Chief Information Officer Consortium 2011), the point estimates suggest that EMR systems, at least, earn back their operating costs.[13] Most significantly, these findings apply primarily to the population of nursing homes that have complementary work design.

The results of the cost-function analysis are shown in Table 3. Although some evidence can be seen of a small positive effect of EMR adoption on costs (meaning that EMR-system adoption leads to a slightly higher operating cost), none of these estimates is significant at conventional levels. A positive effect of work organization in isolation can be seen (+2.3%, $p < 0.05$), but this is almost completely offset in nursing homes that adopt EMR systems.[14] Therefore, the cost-function analysis is inconclusive as to whether EMR systems have any effect. Overall, EMR systems appear to generate sufficient financial incentives to motivate their adoption but only for nursing homes with complementary work organization.

## Efficiency Analysis

The results of the efficiency analysis are shown in Table 4. Columns (1) and (2) show the baseline estimates (one with Huber–White standard errors and the other with bootstrap errors). This analysis suggests that facilities that use EMR systems are about 1.6% more efficient, although this is not statistically significant except when bootstrap errors are used (although this is

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[13] The exact return depends heavily on how much of the EMR costs are reimbursed. Once the productivity gain exceeds expected operating costs, however, the benefits of EMR outweigh the costs regardless of whether they are included in the reported costs, reimbursed, or not included at all. The worst case is that they are not included, so a 0.5% return is break-even under any set of assumptions.

[14] The marginal effect of work organization post-adoption of EMR is 2.3% [for WO] − 1.2% [for UseEMR*WO] − 1.0% [for AfterEMR* WO] = 0.1%.[[**AU: Please verify that the changes are correct.]]**

not conclusive because of the inability to correct for repeated observations). The results rise slightly when work organization controls are included.

As with the cost-function analysis, although the direct effect of work organization is negative (−2.0%), this effect is brought to 0 or even a slightly positive effect for eventual EMR adopters.[15] Thus, to the extent that these work practices are costly to implement but provide benefits in other ways (e.g., improved staff satisfaction or retention), the use of EMR systems essentially pays for these costs, at least in terms of efficiency. The control variables are largely consistent with the productivity results after we account for differences in how output is measured.[16]

## Quality Outcomes

In a final set of tests, shown in Table 5, we estimate how EMR-system adoption has affected a battery of other nursing home variables, using the fixed-effects specification described in the context of Table 1. The variables on the lefthand side of Table 5 are dependent variables. Overall, we find that staffing (both overall and the number of nurses) and quality (complaints, deficiencies, and quality score) are essentially unchanged after EMR-system implementation. A slight shift away from Medicaid residents and toward Medicare and private-pay residents is apparent, but the effects are small. This suggests that a more profitable resident mix may be possible, but no fundamental reason exists for the system to facilitate an increase in Medicare-reimbursed rehabilitation residents. This shift is also consistent with about a $5 increase in the

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[15] The direct effect of work organization is −2.0%. If the nursing home is an eventual EMR adopter, these work practices have no net effect on efficiency:−2.0% [for work organization] + 2.4% [for AdoptEMR*HPWS] + 0.9% [for AfterEMR*HPWS] = 1.3%. (HPWS stands for high-performance work systems.**[[AU: Please verify (1) changes are correct and (2) full form for HPWS xx- yes these are both okay -xx]].**)

[16] The NYMetro variable is negative here and positive in the productivity analysis because the efficiency analysis is based on residents served and not on revenue (which is higher in New York City per resident).

average daily rate. Finally, we find that gross margin increases significantly (about a 1.9% increase) after EMR-system implementation. Of these results, the most important are perhaps the quality-related results, which suggest no measurable quality improvement occurs. Whether this is attributable to the lack of any effect, a potential for long lags between implementation and quality effects, or measurement issues is unknown. Note, however, that long-term care has a history of operational enhancements being associated with an erosion in care quality, so a neutral impact on the quality measures may be actually be a "good" result in the context of this industry.

## Conclusion

Overall, we find support for the argument that the implementation of EMR systems improves productivity and efficiency, especially in facilities that implement or previously had IT-complementary work organization. HIT systems will probably continue to diffuse across nursing homes. Given that no clear negative impact on quality and some evidence of increases in productivity can be seen, we expect this trend to continue and lead to measurable increases in overall nursing home performance. Our results suggest that financial benefits exist to shifting to the greater use of work systems that prioritize collaboration and decentralized decision making concurrently with the implementation of EMR systems.

We note two important implications of our findings: the first regarding the debate on public funding of HIT in nursing homes and the second regarding complementarities between HIT and work design. Our study provides evidence that the benefits of EMR implementation in nursing homes are distributed among owners of nursing homes, payers, and residents. For the owners, the returns appear to be large enough to provide nursing home operators with incentives to adopt these technologies, at least in nursing homes that have adopted modern workplace practices. Based on our findings, we expect federal funding to have, at least, a neutral effect on patients. Moreover, EMR use should also improve not only productivity, which acts as a transfer, but also efficiency, which suggests welfare gains. Overall, the productivity and efficiency analysis suggests about a \$3 to \$5 increase in operating margin per bed-day for the direct effect and a similar additional amount for facilities that use complementary work organization; this is modest but apparently greater than the expected implementation and operating costs of the technology. Moreover, these benefits may be higher if some of the costs can be recaptured through the prospective payment system.

From a social standpoint, the results are more mixed. Productivity benefits incorporate increases in revenue as well as costs, so they are not necessarily a good guide for social investment decisions because they combine revenue enhancements, which are transfers, with efficiency gains, which increase welfare. Coupled with the observation that nursing homes that have invested in EMR systems have a higher average reimbursement rate (and a higher Medicare and private-pay resident mix), a substantial portion of the benefit may be coming from higher revenues rather than reduced costs. Nevertheless, because nursing homes cannot discriminate between the care they give to residents based on their different payers, investments that make the home more attractive to Medicare and private-pay residents, who have greater choices about which facility they enter, will most likely improve the quality of care for all residents, possibly in ways that cannot be easily captured by our aggregate quality measures.

A second implication of this study is related to complementarities between HIT and work design. Our findings indicate that EMR systems amplify the importance of the work practices that prior literature has shown to lead to improved health care quality. Our analyses suggest that these work practices are associated with slightly higher costs and lower efficiency for the owners of nursing homes but that these drawbacks are largely offset in homes that use EMR systems. Therefore, we expect the diffusion of HIT to lead to the greater use of these work practices relative to their pre-HIT baseline, which will have benefits for residents.

Our study has several limitations, some of which present avenues for future research. First, our sample is drawn from nursing homes in New York State. These homes may differ in terms of workforce or patient mix in ways that make extending our results to other nursing homes difficult, although our difference-in-differences specification addresses some of the potential issues in this area. Second, our survey approach treats work-organization measures as static, so to the extent that these practices change significantly during our sample period, our measures may be subject to some amount of error. Third, although we consider several outcomes, EMR systems can generate value for other stakeholders. For instance, significant benefits can be captured through EMR systems if their use leads to fewer emergency room or doctor visits by nursing home residents. Finally, to the extent that some adjustments may take a longer time to implement, the long-run effects of EMR systems may differ from the short-run effects estimated in our study.

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*Table 1*. Sample Characteristics

| | *(1)* Sample average, 2009 | *(2)* Difference-in-differences[a] | *(3)* Significance level |
|---|---|---|---|
| Adoption variable | | | |
| UseEMR | 63.0% | | |
| | | | |
| Production variables (millions of dollars) | | | |
| Output | $16.48 | 1.21% | n.s. |
| Value-added | $15.03 | 1.20% | n.s. |
| Employment expense | $9.03 | −1.99% | $p < 0.01$ |
| Materials and services | $5.48 | 0.40% | n.s. |
| Bed size | 167.9 | −0.81% | $p < 0.01$ |
| | | | |
| Employment variables | | | |
| Employment | 181.6 | −1.07% | n.s. |
| Number of nurses (RNs and LPNs) | 107.5 | −1.02% | n.s. |
| | | | |
| Quality measures | | | |
| Quality score | 75.1 | −0.4 | n.s. |
| Complaint score | 11.4 | 2.24 | n.s. |
| Deficiency score | 21.5 | 2.2 | n.s. |
| | | | |
| Prices | | | |
| Medicare | $455.76 | $2.60 | n.s. |
| Medicaid | $210.16 | −$0.93 | n.s. |
| Overall | $285.55 | $4.86 | $p < 0.10$ |
| | | | |
| Margins | | | |
| Gross margins | 9.02% | 1.94% | $p < 0.01$ |
| Gross margins (after administrative costs) | 7.25% | 1.97% | $p < 0.01$ |
| | | | |
| Other controls | | | |
| For-profit | 57.0% | 0.71% | n.s. |
| Unionized | 63.0% | 1.01% | n.s. |
| NYMetro | 28.6% | 0.24% | $p < 0.01$ |
| Medicare | 11.5% | 0.42% | $p < 0.01$ |
| Medicaid | 73.3% | −0.73% | n.s. |
| Competition index | 6.4% | 0.19% | n.s. |
| | | | |
| Number of facilities | 304 | | |

*Notes:* EMR, electronic medical record system; n.s., not significant.
[a] Coefficient estimates from the difference-in-differences estimator (pre-adoption compared to post-adoption) from Equation (1) using the row variable as the dependent variable.

*Table 2.* EMR Adoption and Nursing Home Productivity

| *Variables* | *(1)* *VA* *Baseline* | *(2)* *VA* *DID*[a] | *(3)* *VA* *DID WO* | *(4)* *VA* *RE* | *(5)* *VA* *FE* | *(6)* *VA* *Quantile regressions* |
|---|---|---|---|---|---|---|
| UseEMR | | −0.008 | −0.007 | −0.009 | | −0.002 |
| | | (0.010) | (0.010) | (0.010) | | (0.006) |
| AfterEMR | | 0.014 | 0.014 | 0.018*** | 0.019*** | 0.016** |
| | | (0.010) | (0.010) | (0.006) | (0.006) | (0.007) |
| WO | | | −0.011 | −0.007 | | −0.007 |
| | | | (0.008) | (0.008) | | (0.005) |
| UseEMR *WO | | | 0.002 | 0.001 | | −0.005 |
| | | | (0.010) | (0.010) | | (0.006) |
| AfterEMR*WO | | | 0.019*** | 0.015*** | 0.015*** | 0.019*** |
| | | | (0.007) | (0.005) | (0.005) | (0.006) |
| log(Labor Expenses) | 0.620*** | 0.620*** | 0.622*** | 0.576*** | 0.473*** | 0.629*** |
| | (0.021) | (0.021) | (0.020) | (0.013) | (0.020) | (0.011) |
| log(Materials Expenses) | 0.325*** | 0.325*** | 0.325*** | 0.320*** | 0.282*** | 0.314*** |
| | (0.011) | (0.011) | (0.011) | (0.008) | (0.011) | (0.007) |
| log(Capacity) | 0.066** | 0.065** | 0.063** | 0.113*** | 0.147*** | 0.067*** |
| | (0.027) | (0.027) | (0.027) | (0.016) | (0.034) | (0.011) |
| For-profit | 0.024** | 0.026** | 0.026** | 0.017* | 0.017 | 0.021*** |
| | (0.010) | (0.010) | (0.011) | (0.010) | (0.022) | (0.007) |
| Unionization | −0.020* | −0.019 | −0.018 | −0.023*** | −0.020* | −0.010 |
| | (0.011) | (0.011) | (0.011) | (0.009) | (0.012) | (0.007) |
| Quality score | −0.018 | −0.018 | −0.018 | −0.023* | −0.023 | −0.012 |
| | (0.018) | (0.018) | (0.018) | (0.014) | (0.015) | (0.014) |
| Complaint score | −0.009*** | −0.008*** | −0.008*** | −0.009*** | −0.008*** | −0.006*** |
| | (0.003) | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) |
| Deficiency score | −0.005* | −0.005** | −0.005* | −0.002 | −0.001 | −0.004** |
| | (0.003) | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) |
| NYMetro | 0.027** | 0.028** | 0.028** | 0.046*** | 0.047 | 0.025*** |
| | (0.014) | (0.014) | (0.013) | (0.013) | (0.047) | (0.009) |
| %Medicare | 0.255*** | 0.254*** | 0.254*** | 0.456*** | 0.606*** | 0.143** |
| | (0.087) | (0.087) | (0.088) | (0.067) | (0.085) | (0.059) |
| %Medicaid | −0.142*** | −0.141*** | −0.138*** | −0.102*** | −0.050 | −0.167*** |
| | (0.051) | (0.052) | (0.051) | (0.039) | (0.056) | (0.030) |
| Herfindahl index | 0.000 | 0.008 | 0.006 | −0.059 | −0.055 | −0.005 |
| | (0.056) | (0.056) | (0.059) | (0.048) | (0.054) | (0.048) |
| | | | | | | |
| Number of observations | 1,999 | 1,999 | 1,999 | 1,999 | 1,999 | 1,999 |
| $R^2$ | 0.980 | 0.980 | 0.980 | | 0.692 | |

*Notes:* The dependent variable in all regressions is the log of value-added (sales minus materials). Robust standard errors are reported in parentheses. DID, difference-in-differences; EMR, electronic medical record system; FE, fixed effects; log $P_S$, ; RE, random effects; VA, value-added; WO, work organization.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

[a] Difference-in-differences regression comparing the change in performance of homes pre- and post-adoption or against changes in performance for homes that never adopted EMR.

*Table 3.* EMR Adoption and Nursing Home Costs

| | *Dependent variable: Labor demand* | | *Dependent variable: Total variable costs* | |
|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* |
| | | | | |
| *Variable* | *EMR* | *EMR × WO* | *EMR* | *EMR × WO* |
| UseEMR | −0.001 | −0.001 | −0.009 | −0.008 |
| | (0.006) | (0.006) | (0.014) | (0.014) |
| AfterENR | −0.000 | −0.001 | 0.006 | 0.005 |
| | (0.005) | (0.005) | (0.011) | (0.011) |
| WO | | 0.007 | | 0.023** |
| | | (0.005) | | (0.011) |
| UseEMR*WO | | −0.003 | | −0.012 |
| | | (0.006) | | (0.013) |
| AfterEMR*WO | | −0.002 | | −0.010 |
| | | (0.003) | | (0.008) |
| log(Medicare Days) | −0.003 | −0.003 | 0.093*** | 0.094*** |
| | (0.007) | (0.007) | (0.013) | (0.013) |
| log(Medicaid Days) | −0.017 | −0.017 | 0.436*** | 0.431*** |
| | (0.015) | (0.015) | (0.060) | (0.060) |
| log(Private Pay Days) | 0.017*** | 0.018*** | 0.147*** | 0.148*** |
| | (0.005) | (0.005) | (0.014) | (0.014) |
| log(Capacity) | −0.017 | −0.018 | 0.267*** | 0.272*** |
| | (0.021) | (0.022) | (0.080) | (0.080) |
| For-profit | −0.031*** | −0.031*** | −0.084*** | −0.084*** |
| | (0.006) | (0.006) | (0.014) | (0.014) |
| Unionization | 0.007 | 0.009 | 0.001 | 0.004 |
| | (0.007) | (0.007) | (0.014) | (0.014) |
| Quality score | 0.000 | 0.000 | 0.000 | 0.001 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Complaint score | 0.001 | 0.001 | 0.003 | 0.003 |
| | (0.001) | (0.001) | (0.003) | (0.003) |
| Deficiency score | −0.005*** | −0.005*** | −0.009*** | −0.009*** |
| | (0.001) | (0.001) | (0.003) | (0.003) |
| NYMetro | 0.005 | 0.005 | 0.014 | 0.013 |
| | (0.009) | (0.009) | (0.020) | (0.020) |
| Herfindahl index | −0.037 | −0.032 | −0.033 | −0.015 |
| | (0.035) | (0.035) | (0.085) | (0.085) |
| Services | 0.003*** | 0.004*** | 0.009*** | 0.009*** |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| log (Labor Price) | 0.144*** | 0.142*** | | |
| | (0.018) | (0.018) | | |
| log(Materials Price) | −0.164*** | −0.164*** | | |
| | (0.012) | (0.013) | | |
| | | | | |
| Number of observations | 1,999 | 1,999 | 1,999 | 1,999 |
| $R^2$ | 0.640 | 0.642 | 0.960 | 0.960 |

*Notes:* The translog cost function also contains first-order (linear), squared, and interaction terms between all inputs and outputs (not shown but available upon request). Robust standard errors appear in parentheses. EMR, electronic medical record system; log $P_w$, ; log$_Y$, log $P_m$; WO, work organization.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

*Table 4.* EMR Adoption and Nursing Home Efficiency

| *Variables* | *(1)* *DEA* *Baseline* | *(2)* *DEA* *Baseline bootstrap* | *(3)* *DEA* *WO* | *(4)* *DEA* *WO bootstrap* |
|---|---|---|---|---|
| UseEMR | 0.016 | 0.016** | 0.016 | 0.016** |
| | (0.018) | (0.008) | (0.018) | (0.007) |
| AfterEMR | 0.016 | 0.016** | 0.017 | 0.017** |
| | (0.013) | (0.007) | (0.013) | (0.007) |
| WO | | | −0.020 | −0.020*** |
| | | | (0.016) | (0.006) |
| UseEMR*WO | | | 0.024 | 0.024*** |
| | | | (0.017) | (0.007) |
| AfterEMR*WO | | | 0.009 | 0.009 |
| | | | (0.011) | (0.006) |
| For-profit | 0.072*** | 0.072*** | 0.074*** | 0.074*** |
| | (0.017) | (0.007) | (0.017) | (0.008) |
| Unionization | −0.010 | −0.010* | −0.012 | −0.012* |
| | (0.014) | (0.006) | (0.015) | (0.006) |
| Complaint score | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Deficiency score | −0.000 | −0.000 | 0.000 | 0.000 |
| | (0.000) | 0.000 | (0.000) | (0.000) |
| NYMetro | −0.045** | −0.045*** | −0.043** | −0.043*** |
| | (0.022) | (0.010) | (0.022) | (0.008) |
| Herfindahl index | 0.220*** | 0.220*** | 0.221*** | 0.221*** |
| | (0.078) | (0.033) | (0.077) | (0.030) |
| | | | | |
| Number of observations | 1,875 | 1,875 | 1,875 | 1,875 |
| $R^2$ | 0.115 | 0.115 | 0.123 | 0.123 |

*Notes:* All estimates are from a data envelopment analysis. The dependent variable in all regressions is the Efficiency score, computed based on the homes outputs and input use. Columns (1) and (3) use Huber-White standard error, and columns (2) and (4) use bootstrap errors. Robust standard errors appear in parentheses. DEA, data envelopment analysis; EMR, electronic medical record system; WO, work organization.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

*Table 5.* EMR Adoption and Additional Nursing Home Outcome Variables

| *Dependent variable* | *Post-adoption EMR* | *Standard error* | *Number of observations* | $R^2$ |
|---|---|---|---|---|
| log(FTE) | −0.011 | (0.008) | 2,748 | 0.005 |
| log(Nurses) | −0.010 | (0.010) | 2,748 | 0.002 |
| Price Medicare[a] | 2.604 | (4.529) | 2,393 | 0.627 |
| Price Medicaid[b] | −0.937 | (1.285) | 2,040 | 0.308 |
| Price overall[c] | 4.860* | (2.688) | 2,667 | 0.267 |
| Gross margin | 0.019*** | (0.005) | 2,748 | 0.011 |
| %Medicare | 0.004** | (0.002) | 2,748 | 0.010 |
| %Medicaid | −0.007** | (0.003) | 2,748 | 0.032 |
| %Private | 0.003 | (0.002) | 2,748 | 0.037 |
| Complaint score | 2.237 | (2.236) | 2,748 | 0.004 |
| Deficiency score | 2.165 | (2.049) | 2,748 | 0.012 |
| Quality score | −0.348 | (0.650) | 2,748 | 0.007 |

*Notes:* The estimate in each row is from a difference-in-differences estimator similar to the one shown in Equation (1). EMR, electronic medical record system; FTE, full-time employment.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. The dependent variable for each row is as follows:

[a] Revenue per Medicare patient.

[b] Revenue per Medicaid patient.

[c] Revenue for all patients.