Does Technology Substitute for Nurses? Staffing Decisions in Nursing Homes[*†]

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Abstract

Over the past ten years, many healthcare organizations have made significant investments in automating their clinical operations, mostly through the introduction of advanced information systems. Yet the impact of these investments on staffing is still not well understood. In this paper, we study the effect of IT-enabled automation on staffing decisions in healthcare facilities. Using unique nursing home IT data from 2006 to 2012, we find that the licensed nurse staffing level decreases by 5.8% in high-end nursing homes but increases by 7.6% in low-end homes after the adoption of automation technology. Our research explains this by analyzing the interplay of two competing effects of automation: the substitution of technology for labor and the leveraging of complementarity between technology and labor. We also find that increased automation improves the ratings on clinical quality by 6.9% and decreases admissions of less profitable residents by 14.7% on average. These observations are consistent with the predictions of an analytical staffing model that incorporates technology adoption and vertical differentiation. Overall, these findings suggest that the impact of automation technology on staffing decisions depends crucially on a facility's vertical position in the local marketplace.

Key Words: staffing, labor, automation technology, vertical differentiation, nursing homes

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1. Introduction

Will improved technology provide enough jobs? In a recent Wall Street Journal article, former U.S. Treasury Secretary Lawrence Summers voiced such a concern.[1] Microsoft co-founder Bill Gates warned in 2014 that automation threatens all manners of workers, from drivers to waiters to nurses.[2] Similarly, but in a more optimistic tone, Marc Andreessen,[3] a well-known entrepreneur and software engineer, said in an interview that "software will eat the world," to express his view that information technology will revolutionize all sectors of the economy, replacing old jobs with new jobs along the way.

Over the past ten years, advances in information technology have been changing healthcare delivery by bringing digitization and automation into the industry. As more and more healthcare providers adopt technologies such as computerized provider order entry (CPOE), the administration and delivery of care become streamlined and efficient (Agarwal et al. 2010; Goh et al. 2011). As a result, policy makers and medical providers, especially nurses, want to know: does technology substitute for nurses, the basic labor force in the healthcare industry? In this study, we aim to address the technology-nurse relation from a strategic-positioning perspective. Although the relation between technology and nurse employment has generated considerable interests among the public, the literature investigating the effect of IT-enabled automation on staffing decisions in individual facilities is relatively sparse.

We choose nursing homes as our study subjects. Compared to hospitals, nursing homes provide a relatively clean setting to address the relation between technology and labor, as both the structure of labor provision and the services are relatively homogeneous (Norton 2000). Quality of care in a nursing home is mainly determined by nurses on a daily basis. IT-enabled automation may help reduce nurse tasks, increase the utilization of nurse time, improve the working environment for nurses and strengthen the bonds between nurses and residents. Interestingly, adoption of IT-enabled automation has largely lagged behind in nursing homes compared to other healthcare facilities such as hospitals. According to Health Information Management Systems Society (HIMSS) data, more than 80% of hospitals had adopted CPOE by 2011 while less than 40% of nursing homes had implemented it.

We use the adoption of CPOE, an advanced information system, to measure the level of IT-enabled automation in nursing homes. CPOE can help healthcare providers streamline operations via automation, reduce medication errors, and improve resident safety (Davidson and Chismar 2007). Using the Online Survey Certificate and Reporting (OSCAR) nursing home data and the one-year lagged HIMSS CPOE data from 2006 to 2012, we find that automation has no effect on overall labor demand, but its effect on staffing decisions depends crucially on a nursing home's vertical position in the local market. Our results show that

[1] http://www.wsj.com/articles/lawrence-h-summers-on-the-economic-challenge-of-the-future-jobs-1404762501
[2] http://www.wsj.com/articles/what-clever-robots-mean-for-jobs-1424835002
[3] http://www.wired.com/2012/04/ff_andreessen/5/.

the licensed nurse (LN) staffing level increases on average 7.6% in low-end nursing homes but decreases by 5.8% in high-end homes after CPOE is adopted. The outcomes can be explained by the interplay of two competing effects of IT-enabled automation. On one hand, automation increases the marginal benefit of quality improvement from increased staffing. This *complementarity* effect helps a nursing home improve its competitiveness in its local market (McAfee and Brynjolfsson 2008). On the other hand, the marginal effect of quality on revenue diminishes as quality improves. Given that the marginal cost of staffing is relatively constant, an increase in automation may actually lead to the substitution of technology for labor, which we call the *substitution* effect. The complementarity effect dominates the substitution effect in low-end nursing homes, but is dominated by the latter in high-end ones.

Further, we find that an increase in automation leads to an increase in resident clinical outcomes. The results show that ratings on clinical quality increase by 6.9% on average after a nursing home implements CPOE, all else being equal. Interestingly, although CPOE adoption does not change the total number of admissions, possibly due to capacity limits, it does result in a 14.7% decrease in the admissions of Medicaid residents, the least-profitable type, regardless of a nursing home's vertical position. These results echo current industry trends, in which nursing homes strive for quality improvement as they chase lucrative residents.[4] Moreover, all these empirical findings are consistent with the predictions of a staffing model that incorporates technology adoption and vertical differentiation. To the best of our knowledge, this is the first paper in the health IT literature that theoretically and empirically addresses the impact of automation technology on nurse labor from a strategic-positioning perspective.

2. Industry Background and Literature Review

A nursing home is a place for the elderly or the disabled who do not need to be in a hospital but still require assistance in daily living activities and/or medical care from professional nurses. Due to the aging of the baby boomer generation, approximately $111 billion was spent on nursing home care in the United States in 2011, up from $92 billion in 2006.[5] The entire nursing home industry is very competitive (Lu and Wedig 2013). According to the OSCAR data, on average, there are 13.7 nursing homes located within a five-mile radius of each other. Compared to hospitals, nursing homes provide relatively homogeneous services, and quality is mainly determined by the nurses. They thus provide an ideal setting to investigate the relation between automation technology and staffing input.

[4] http://omnifeed.com/article/www.nytimes.com/2015/04/15/business/as-nursing-homes-chase-lucrative-patients-quality-of-care-is-said-to-lag.html

[5] http://www.ltlmagazine.com/news-item/ltc-industry-generates-259-billion-revenue-during-2011

2.1 Quality Mix and Vertical Differentiation

Nursing home services are mainly paid for in one of three ways: Medicare, Medicaid, or private-pay.[6] Post-acute care services are generally paid by Medicare or private insurers, and long-term care (LTC) services are largely paid by Medicaid. Currently, Medicare residents generate the highest per-resident revenue and profit margins (average revenue of around $500 per resident per day) while Medicaid residents generate the lowest (average daily revenue under $194).[7] Hence, a nursing home is often assessed in terms of its "quality mix," which is an industry jargon defined as the percentage of revenues from sources other than Medicaid (Credit Suisse Equity Research 2001).

Nursing homes generally prefer payment sources such as private-pay or Medicare due to their high margins and these non-Medicaid patients typically gain admission first when there are not enough beds (Nyman 1993). Although nursing homes are not allowed to discriminate among residents based on their payer types after admission (Grabowski et al. 2008), nursing homes can (and do) screen applicants before admission. Federal and state regulations do not allow nursing homes to demand cash payment before they accept a Medicaid resident or to ask the family of a resident to sign a so-called private-pay duration-of-stay clause which requires the resident not to use Medicaid for certain amount of time.[8] However, nursing homes have varying degrees of flexibility to choose who they admit and are typically not required to justify to the applicant why she is not admitted.[9] In fact, the main driver of quality competition among nursing homes is attracting residents who are willing to pay more for better quality of care (Cohen and Spector 1996; Chen and Grabowski 2015).

Given the importance of quality of care in competition for high-margin residents, vertical differentiation in service quality naturally becomes an important feature of the nursing home industry and is directly reflected by the star rating system provided by the federal Nursing Home Compare (NHC) website (Konetzka et al. 2015).[10] The NHC also publicly releases nurse-to-resident staffing ratios to help

[6] The distribution of the three types of residents in 2006 was Medicaid, 64.8%, Medicare, 13.4%, and privately paying, 21.0%.
[7] These daily rates are taken from the quarterly report filed by Genesis Healthcare on May 8, 2015. Medicare pays for the first 20 days at full cost, and the difference between $114 per day and the actual cost for up to another 80 days (The BBA of 1997).
[8] Because of nursing homes' strong incentives to admit applicants with more payments from sources other than Medicaid, such practices were in fact quite prevalent. The U.S. congress special committee on aging held a public hearing on "discrimination against the poor and disabled in nursing homes" in 1984 to investigate this issue. According to one witness named Jody Moser who used to work as the admission director of a nursing home in Tennessee, they kept two waiting lists, one for private pay and one for Medicaid, and they took Medicaid when they could not fill a bed with private pay. For more details, please see the hearing record at http://www.aging.senate.gov/imo/media/doc/publications/1011984.pdf.
[9] Different states have different rules regarding nursing home admissions. For example, the rule of the State of New York states that "each nursing home is required to develop an admission policy and procedure that is in accordance with state and federal regulations and does not unlawfully discriminate against applicants. However, nursing homes have discretion in making admission decisions and are not required to admit every applicant."
[10] For example, HCR Manor Care is a company with many high-end nursing homes. It owns a premium brand name, Manor Care, with most of its units rated five stars. By contrast, Kindred, which is one of the largest nursing home chains, mainly targets Medicaid residents and provides relatively lower quality of care. Hence, most of its units are low-end nursing homes rated three stars. Corresponding to this vertical position strategy, Kindred seldom uses a brand name for its individual units so as to minimize the negative externality across sibling units (Brickley et al. 2016).

consumers identify high-quality nursing homes. Konetzka et al. (2008) show that high staffing ratios are positively associated with high quality in nursing homes. Naturally, nurse input serves as a critical proxy for quality. Interestingly, the variation of nurse-to-resident staffing ratios is very large across nursing homes (Chen 2008). According to the 2006 staffing information released by the NHC, the dispersion of LN hours per resident day (HPRD) between 1 percentile and 99 percentile is 4.59, suggesting that nursing homes offer services at different quality levels and target different consumer segments.

2.2 Technology and Workflow

CPOE has long been regarded as a powerful technology to reduce medication errors and to increase efficiency in medication administration.[11] It affects the workflow of both physicians and nurses by replacing traditional methods of placing medication orders (e.g., paper prescriptions, verbal, and fax) with an integrated electronic system. Eisenberg and Barbell (2002) outlined the eight steps to optimize physician workflow using CPOE. Niazkhani et al. (2009) reviewed the literature on the effects of CPOE and highlighted the workflow advantages such as legible orders, remote accessibility of the system, and the shorter order turnaround time. Specific impact of CPOE on nurses, however, is less well understood.

Traditionally, nurses are swamped with tasks such as hunting for supplies, tracking down medications, filling out paperwork at the nurse station, and looking for missing test results. According to Worth (2008), most nurses spend less than half of their time helping patients. A Novant health study found, in a 2010 internal audit for Presbyterian Medical Center, that nurses were involved in direct patient care at the bedside for only 2.5 hours in each 12-hour shift.[12] Clearly, the use of expensive professional nursing time is very inefficient. Moreover, the wasted time is frustrating for nurses, which might lead to poor care for patients. The Novant analysis shows that bedside time got a boost after automation technology was installed. At Presbyterian Medical Center, the implementation of automation technology reduced by 42 minutes the amount of time spent paging other nurses, copying and faxing, and tracking down tests.

Ground (2008) compares the amount of time that nurses spent performing different task groups for paper-based and CPOE ICUs during observations of roughly 32 hours. She finds that the amount of time spent by nurses on the conversational task group decreased from 671.22 minutes (paper-based) to 490.86 minutes (CPOE-based) and the time spent by nurses on the documentation/reading task group decreased from 427.47 (paper-based) minutes to 322.42 minutes (CPOE-based), suggesting the enhanced productivity resulting from the adoption of CPOE. One of the nurses interviewed in Ground (2008) made the following

[11] https://healthit.ahrq.gov/ahrq-funded-projects/emerging-lessons/computerized-provider-order-entry-inpatient/inpatient-computerized-provider-order-entry-cpoe

[12] See the *Wall Street Journal* article, "Better Care at Your Bedside," published on July 21, 2014. The source of Novant health study is the 2013 Novant nursing annual report, which can be downloaded at: https://www.novanthealth.org/Portals/92/novant_health/documents/careers/nursing/2013-charlotte-nursing-annual-report.pdf

comment on CPOE: "*Making nursing job easier. Not trying to find chart with orders. Not trying to decipher handwriting. Don't have to enter orders. Decreased stress because job is clear.*"

The benefits of CPOE in nursing homes have also been studied. Besides the potential benefits of reducing medical errors, CPOE increases labor flexibility via process improvement (Felan et al. 1993). Subramanian et al. (2007) point out that in LTC facilities with CPOE, nurses are likely to spend less time placing orders directly, less time verifying drugs with order, less time identifying, locating, and preparing drugs, less time administering drugs, and less time documenting administration of drugs. For example, under a traditional paper-based system, after a physician writes down prescriptions for residents in a nursing home, nurses at the facility need to transcribe the prescriptions and input them into the facility's system. More often than not, nurses have to communicate with the physician to verify those prescriptions to ensure accuracy and avoid errors. After the physician signs off, the nurses order the medicine from a pharmacy. With CPOE, a physician can directly enter the prescriptions in the computer system, which then sends the medicine orders to the pharmacy electronically and also updates the medical records of the residents. Clearly, the adoption of CPOE can improve prescription efficiency and reduce the workload for nurses.

2.3 Technology and the Nurse Labor Market

The nurse labor market is subject to cycles of shortage and surplus. Since the late 1990s, the market has been characterized by a shortage of nurses, which has triggered a rise in nurses' wages (Rother and Lavizzo-Mourey 2009). After the introduction of the Affordable Care Act which emphasizes prevention and patient experience, nurses tend to play substantial roles. Moreover, with an aging society and the retirement of the baby boomer generation, nurses likely will be in high demand in the long run. The Bureau of Health Professions estimates that the shortage of nurses in the United States will grow to 800,000 vacancies by 2020.

As we discussed in the previous section, technology can significantly enhance nurses' productivity. For example, documenting resident health conditions is a significant part of many nurses' job. Nurses routinely spend 15-25% of their workday documenting resident care, and in some cases considerably more (Gugerty et al. 2007). Information technology can reduce redundant documentation and streamline the collection and retrieval of resident information, thus increasing the efficiency of the entire nursing workforce. In fact, the National Advisory Council on Nurse Education and Practice (NACNEP) recognized that IT can address the nursing shortage and key challenges related to nurse productivity (NACNEP report 2009). The nurse workforce is aware of the impact of health information technology on their careers. For example, in an article titled "Here comes trouble – top 5 healthcare trends RNs must know," which was published in the January/February 2014 issue of *National Nurse*, the rollout of electronic health records systems was identified as one of the dangerous trends that nurses must know about. It was argued that health

IT will "maximize earnings by limiting healthcare providers' use of independent judgment in treatment options" and "ultimately remove people—face-to-face contact—from healthcare."

2.4 Literature Review

Our work contributes to the health IT literature. A large branch of this literature investigate the impact of health IT adoption on quality or health outcomes offered by medical providers (Athey and Stern 2002; Parente and McCullough 2009; Miller and Tucker 2011; Bhargava and Mishra 2014). Besides, Dranove et al. (2014) study the cost savings of health IT adoption. Niazkhani et al. (2009) review studies about the effect of the adoption of CPOE on clinical workflows. Lee et al. (2013) use a production function correcting for endogenous input choices to estimate the impact of health IT investment on productivity. Surprisingly, there are few papers in this literature studying the effect of health IT adoption on nurses, the major labor force in the healthcare market.

More broadly, our work relates to the literature about the impact of technology on *labor market*, which has interested economists long before the emergence of information technology (Griliches 1969). The invention and widespread use of computer technology over the past half century has largely fueled this interest, especially with respect to the impact of technology on wage inequality. In particular, the rising wage inequality since the 1980s has been attributed to a rise in the demand for highly skilled workers due to a burst of new technology -- the hypothesis known in the literature as the Skill-Biased Technical Change (SBTC) hypothesis. Using data from the Annual Survey of Manufactures, the Census of Manufactures, and the NBER trade data, Berman et al. (1994) investigated the shift in demand away from unskilled and toward skilled labor in U.S. manufacturing over the 1980s and concluded that production labor-saving technological changes were the chief explanation for this shift. Autor et al. (1998) found that the strong and persistent growth in relative demand favoring college graduates from 1940 to 1996 is related to the intensity of computer usage. Krusell et al. (2000) considered a four-factor production function and their estimations suggest that declining price of equipment capital can explain a large share of the rise in relative demand for skilled workers in the United States. Acemoglu (2002) surveyed many theories and evidences and proposed a unifying framework.

The most relevant paper to ours in this stream of literature is the one by Autor, Levy, and Murnane (2003, hereafter ALM) which focuses on how computerization alters job skill demands. They argue that computer capital substitutes for workers in performing routine tasks and complements workers in performing nonroutine tasks. As we do, they develop an analytical model to derive hypotheses which are then tested using empirical data. Despite some similarities in modeling, there are important differences between the two papers. First, the ALM model is developed for an industry-level analysis. Indeed, the paper suggests that the agent's objective function, a form of the Cobb-Douglas production function, represents

the "production function of a single industry." This is suitable for their study because their empirical strategy is to use the variation in routine-task-intensities among different industries to test the effect of computerization on job skill demand. By contrast, our model is built with individual nursing homes in mind. Therefore, while the ALM model offers a cross-industry macro view of how IT affects demand for labor, our model offers a within-industry micro view of how IT affects demand for labor in individual firms. Second, because of the differences in data granularity and research scope, our model emphasizes the moderating role of vertical differentiation on IT's impact on labor, which clearly is not the focus of the ALM study because their unit of analysis is industry rather than firm. This also partly explains why this aspect is largely overlooked in the literature. Third, the time horizon between the ALM model and our model also differs significantly. Our model is developed with a short-term time horizon in mind, while the ALM is a general-equilibrium model where workers self-select among occupations to clear the labor market.

This study is relevant to a small set of papers examining the substitution of IT resources for labor. Dewan and Min (1997) formulate a CES-translog production function with IT capital, non-IT capital, and labor as inputs, and annual value added by a firm as the output. They find IT capital is a net substitute for ordinary labor in all economic sectors. Chwelos et al. (2010) find that the increasing share of IT investment comes at the expense of labor through labor substitution. Furukawa et al. (2011) estimate a translog production function and find that IT has a substitutability effect on low-skilled labor and an even stronger complementarity effect on higher-skilled workers. Bresnahan et al. (2002) find that computers and skilled labor are relative complements. Our paper contributes to this line of literature in three ways. First, we focus on how vertical differentiation affects the impact of IT adoption on a firm's strategic staffing decisions. Second, we find that the relative strength of substitution and complementary effects shapes the different labor decisions for individual firms within an industry. Third, this is the first paper using the nursing home setting to document the relation between staffing decisions and adoption of automation technology.

3. Hypotheses Development

To develop testable hypotheses, we build a model to analyze a nursing home's optimal staffing decision. We denote by s the number of staff and by d the number of residents. Hence the nurse-to-resident ratio is $r \equiv s/d$. This staffing ratio is a major determinant of the quality of care provided by a nursing home (Konetzka et al. 2008). An important factor that moderates the quality of care provided by a nursing home with a given nurse-to-resident ratio is the degree of IT-enabled automation, which is represented in our model by a positive and continuous number, k. Given the staffing ratio r and the automation level k, the quality of care is $q = Q(r, k)$. We require Q be increasing in both r and k. Note that because the optimal staffing ratio is endogenous, the assumption on the monotonicity of Q does not suggest that an increase in automation will necessarily lead to an increase in quality. For example, if an increase in automation level

k leads to a decrease in staffing ratio r, the overall effect on quality is ambiguous. This monotonicity assumption states that, *ceteris paribus*, nurses equipped with automation technology can work more efficiently in a nursing home and spend more time with residents, thereby providing better care. This assumption is consistent with the empirical evidence on the benefits of IT-enabled automation for nurse productivity and the general view that computerization improves productivity (Brynjolfsson and Hitt 2003).

Although each state's Medicaid program is different, the margin from an average Medicaid resident is generally the lowest compared with Medicare or private-paying residents. Because prices for Medicare and Medicaid residents are heavily regulated by the government, a nursing home's quality of care becomes an increasingly important factor in the competition for profitable residents. To focus on this unique industry characteristic, we model a nursing home's average revenue per resident as a function $R(q,\theta)$ where q is the quality of care offered by the nursing home and $\theta \in [\underline{\theta}, \overline{\theta}]$ is a parameter to introduce heterogeneity among nursing homes. As we show later, a natural interpretation of this parameter θ is a nursing home's brand equity which reflects consumers' perception of its quality.[13] In the short run, a nursing home may be able to adjust its quality level but is unlikely to change consumers' perception about its brand. Because our empirical study focuses on a seven-year sample period, we assume θ is exogeneous during this period. From the modeling perspective, one can think of the value of θ as being picked by nature at the beginning of our study, and each nursing home, after observing its realized θ value, optimally selects the quality level.

We assume that $R(q,\theta)$ is increasing in q, which implies that a nursing home with high quality care has high average revenue per resident. The rationale is that high quality nursing homes are more likely to attract profitable residents than low quality nursing homes.[14] Apparently, $R(q,\theta)$ must satisfy $\lim_{q\to\infty} \partial R/\partial q = 0$ because $R(q,\theta)$ is necessarily capped by the revenue per resident from the most lucrative residents. A stylized way to incorporate this requirement is to assume that $R(q,\theta)$ is concave in q; that is, $\partial^2 R/\partial q^2 < 0$. Finally, we denote the average wage paid to LNs by w.

We assume a fixed occupancy rate, which implies a fixed total number of residents for a nursing home with a given number of beds. [15] The rationale is that nursing homes can fill their vacant beds with Medicaid residents, who are typically in excess demand, and the certificate-of-need (CON) law restricts nursing home expansion (Harrington et al. 1997). This assumption simplifies our analysis and allows us to

[13] In the nursing home industry, "potential customers and key stakeholders form mental images and perceptions of the nursing facilities that they are familiar with, have seen advertised, or have heard about in a media report or from friends and neighbors. People use such perceptions to rank a particular facility and its services in relation to the other facilities in the community. People rank a facility in terms of how favorably they view a given facility" (Singh 2004).

[14] Empirical evidence also suggest that the proportion of Medicare and private-paying consumers is positively correlated with the LN staffing ratio increases. For details, please refer to the online appendix Figure A1 where we plot the distribution of quality mix across 100 quintile licensed nurse (LN) staffing ratios.

[15] The average occupancy rates remain stable over the years in spite of the increasing adoption of CPOE. For details, please refer to the online appendix Figure A1 where we plot nursing home occupancy rates over years. In Section 7.2, we also empirically test this assumption that the total number of residents does not vary after the adoption of CPOE.

focus on the average revenue per resident, which is of particular importance to nursing homes. For ease of notation, we normalize the total number of residents to 1.

To understand how an increase in automation affects the optimal staffing decision and the implication for the quality of care provided, we treat the staffing decision s as the decision variable and treat the automation level k as a parameter. Essentially, we model how a nursing home should optimally determine its quality level by choosing an appropriate staffing level. Mathematically, we can write the surplus revenue optimization problem as follows:[16]

$$\max_{s} \mathrm{V}(s) = R(q,\theta) - ws.$$

Note that because k is not a decision variable in our model, the cost of investing in technology is normalized to 0. We denote the solution to the optimization problem by s^*, and the associated quality of care by q^*. Our analysis examines how an increase in automation level k in a nursing home affects its optimal staffing decision s^* and the implication for the resulting quality q^*. To this end, we assume the following functional forms of $Q(r,k)$ and $R(q,\theta)$:

$$Q(r,k) = rk, \quad R(q,\theta) = \lambda\left(1 - \alpha\theta e^{-A\theta q}\right) + (1-\lambda)\left(1 - \beta\theta e^{-A\theta q}\right)$$

where $\left(1 - \alpha\theta e^{-A\theta q}\right)$ is the average revenue per resident from short-term residents (typically Medicare and private-pay residents), $\left(1 - \beta\theta e^{-A\theta q}\right)$ is the average revenue per resident from long-term residents (typically Medicaid and private-pay residents), and λ and $(1-\lambda)$ are their respective weights.[17] Clearly, $Q(r,k)$ and $R(q,\theta)$ satisfy the following properties:$\partial Q/\partial r > 0$,$\partial Q/\partial k > 0$,$\partial R/\partial q > 0$, $\partial^2 R/\partial q^2 < 0$, and $\lim_{q\to\infty} \partial R/\partial q = 0$. We define $b = \lambda\alpha + (1-\lambda)\beta$ and impose the technical assumption $0 < \underline{\theta} < \overline{\theta} < \sqrt{we^2/Akb}$ which allows us to interpret the parameter θ as the vertical position of a nursing home within its competitive market as is shown in the following result.

Proposition 1: The optimal staffing level s^*, the optimal quality level q^*, and the average revenue per resident $R(q^*,\theta)$ are increasing in θ.

To understand how an increase in automation affects a nursing home's quality and the average revenue per resident, we evaluate the signs of $\partial q^*/\partial k$ and $\partial R(q^*,\theta)/\partial k$ in the next proposition.

Proposition 2: The average revenue per resident $R(q^*,\theta)$ and the optimal quality level q^* are increasing in the automation level k.

[16] About 30% of nursing homes are nonprofit organizations or government owned. However, this does not mean that these organizations do not care about their bottom lines. They differ from for-profit nursing homes by not distributing its surplus income to the organization's directors as profit or dividends. To avoid confusion, we use the term surplus revenue to denote the difference between revenue and expense.

[17] The exponential utility function form is often used in the economics and business literature (Malamud et al. 2013, 2016) to model increasing and concave utility preference. We adapt it here to capture the increasing and concave relation between average revenue per patient and nursing home quality, which gives us nice analytical tractability. Our analytical results can also be obtained using alternative functional forms such as a quadratic function with restricted domain.

Finally, to examine how an increase in automation affects a nursing home's optimal staffing decision, we need to evaluate the sign of $\partial s^* / \partial k$. The following proposition summarizes the results.

Proposition 3: An increase in automation leads to an increase in a nursing home's staffing level if $\theta < \sqrt{we/Abk}$, but it leads to a decrease in a nursing home's staffing level if $\theta > \sqrt{we/Abk}$.

The above result suggests that the effect of automation on the optimal staffing level is more subtle than its effect on the optimal quality level. An increase in automation may lead to an increase or decrease in the optimal staffing level depending on a nursing home's vertical position. Intuitively, the use of automation makes health workers more productive, so the marginal benefit in quality improvement from more staff increases. This *complementarity* effect has its root in the property of the quality function $Q(r,k)$ (i.e., $\frac{\partial^2 Q}{\partial r\, \partial k} > 0$). Because quality improvement eventually translates to a better quality mix and thus higher margin, this complementarity effect of automation encourages a nursing home to increase its staff.

Although an increase in quality leads to a better quality mix and thus increases revenue, the marginal benefit of quality improvement for revenue diminishes as the quality level keeps increasing because the average revenue per resident is concave in quality. The marginal cost of staffing, however, is relatively constant. Thus, for nursing homes that already have high quality (i.e., those with higher values of θ, according to Proposition 1), an increase in automation may actually lead to the substitution of technology for labor. The *substitution* effect has its root in the property of the average price function (i.e., $\frac{\partial^2 R}{\partial q^2} < 0$). The coexistence of the two effects explains the intuition behind Proposition 3: The complementarity effect dominates the substitution effect for low-end nursing homes but is dominated by the substitution effect for high-end nursing homes. We therefore propose the following hypotheses for empirical testing:

Hypothesis 1: An increase in automation leads to a *decrease* in the nurse-to-resident ratio for a nursing home with a high vertical position.

Hypothesis 2: An increase in automation leads to an *increase* in the nurse-to-resident ratio for a nursing home with a low vertical position.

4. Data

This study incorporates two primary data sources: the 2006-2012 OSCAR data and the 2005-2011 HIMSS data. The OSCAR data cover all Medicare- and Medicaid-certified nursing homes operating throughout the United States. The database includes various characteristics (e.g., beds, payer types, resident health status, and staffing information). The HIMSS data provide detailed information on information technology applications adopted by many health facilities, including nursing homes. We manually merged these two datasets using the name, zip code, and phone number of individual nursing homes. In total, we located 2,119 nursing homes and constructed a seven-year, unbalanced panel with 12,313 observations.

In addition, we supplemented the primary data sources with the Skilled Nursing Facility (SNF) cost reports, which offer information on resident admissions (Lu, 2015). We also use the Current Population Survey (CPS) Outgoing Rotation Group Annual Merged Files which provides information on individual working hours, wages and occupation codes. This dataset is the major source for the Bureau of Labor Statistics to derive employment and wage information. The market demographics are obtained from the Area Resource files, which draw health information from an extensive county-level database assembled annually from over 50 sources.[18] Table 1 reports the summary statistics of the key variables. In the following, we describe nursing home staffing measures, vertical position and the adoption of CPOE in detail.

4.1 Staffing Measures and Vertical Position

Generally, a nursing home employs three types of nurses: registered nurses (RNs), licensed practical nurses (LPNs), and certified nurse aides (CNAs). RNs observe, assess, and record residents' symptoms and progress. RNs also collaborate with physicians in treatment, administration of medications, and development of care plans (Konetzka et al. 2008). In many nursing homes, LPNs are primarily responsible for administering medication and serve as imperfect substitutes for RNs for some tasks. (Castle 2008). CNAs provide the bulk of one-on-one care, including assistance with basic life activities such as bathing, dressing, eating, toileting, and walking. In this study, we study all types of nurses with an emphasis on licensed nurses (LNs), including both RNs and LPNs.

The OSCAR data include the total hours worked over a 2-week period for all types of nurses. The OSCAR staffing information is reliable and suitable for our study. The data have been widely used in the health economics literature for various staffing-related studies (Harrington et al. 2000; Lu and Lu 2016). Moreover, the staffing information released by the federal report cards at the Nursing Home Compare is based on the OSCAR data. We therefore use the OSCAR data to calculate HPRD for LNs.

The Omnibus Budget Reconciliation Act of 1987 established minimum staffing standards for nursing homes. The law requires nursing homes to have an RN on duty eight consecutive hours per day for seven days a week and requires a licensed nurse (including both RNs and LPNs) to be on duty for the two remaining shifts each day seven days a week. According to Harrington (2010), for 100 residents, the minimum HPRD for licensed nurses is 0.30 by the federal regulation. Many states have imposed their own requirements concerning minimum staffing standards. Some states set standards higher than the federal ratio, while other states lower the ratio based on their situations. Harrington (2010) converted the different state standards to a uniform format: LN hours per resident day for a 100-bed nursing home. As of 2004, 22

[18] http://www.icpsr.umich.edu/icpsrweb/AHRQMCC/studies/34043.

states had established minimum staffing ratios for licensed nurses that were higher than the federal ratio. The state minimum LN ratios vary considerably across states, and their dispersion is about 1.0 LN HPRD.

Nursing homes with the same staffing levels but located in different states may be positioned differently in their own markets. Fortunately, the state minimum staffing standards provide an exogenous lower bound for the staffing level in each individual market. We use these lower bounds to localize the staffing level for each nursing home. In other words, we define the vertical position for each nursing home as its initial staffing level relative to the imposed state or federal standards. We first calculate the difference between the staffing level in each nursing home and the corresponding state or federal minimum LN staffing ratio for a 100-bed nursing home. Since the staffing level changes with the adoption of CPOE, we use the 2005 staffing data, one year before our sample period, to construct the initial distance for each nursing home, and we name this variable *Position.*[19] Next, we define a binary variable describing vertical quality, *High End*, which equals 1 if the initial distance is above the median of *Position* and 0 if below. This helps us to filter outliers. In the robustness check, we define a relative position measure using a county as a market.

We use the LN staffing ratio instead of other staffing ratios as the benchmark to calculate the initial distance mainly because almost all the states and the federal regulation have minimum staffing standards for LNs, while only a few of them impose separate mandates for RNs, LPNs or CNAs. Using the minimum LN staffing ratio allows us to fully use the national health IT sample. For robustness checks, we also use the minimum RN staffing ratio for normalization.

4.2 CPOE Adoption

CPOE is a sophisticated type of electronic order entry and involves provider entry of orders that are communicated over a computer network to medical staff within an organization and to different health sectors, such as hospitals, nursing homes, and home care providers (Zhang et al, 2016).[20] CPOE also provides error checking for duplicate or incorrect doses or tests. We select CPOE as our subject for two reasons.[21] First, we study the impact of automation technology on labor. CPOE is a great candidate as it links different medical personnel within a nursing home automatically, which significantly reduces hours spent on clinical documentation and changes traditional work practices. Second, CPOE has been adopted relatively recently, and there have been large variations in the adoption decisions across nursing homes

[19] An alternative way to define the vertical position is to use the star ratings. Unfortunately, the star ratings are only available since December 2008. The ratings of some nursing homes are contaminated because they had adopted CPOE by then.
[20] During the sample period, CPOE was mainly used across medical providers within an organization. Some nursing homes can communicate with their affiliated hospitals or local health providers using the software provided by the vendor Epic (Li 2014). In this study, we focus on the intra-organization information system.
[21] EMR is another good candidate. Unfortunately, the HIMSS data recorded EMR adoption information only until 2008. The health IT adoption environment changed significantly after the passage of the Recovery Act.

over the years. In 2005, only 9.4% of nursing homes had adopted CPOE, and just 31.8% had done so by 2011.

5. Empirical Methods

5.1 Specification for Average Effect

We assess the effect of CPOE adoption on nursing home staffing decisions using the following specification, where the unit is a nursing home in a specific year:

$$Y_{ist} = \alpha_0 + \alpha_1 IT_{is,t-1} + \alpha_2 X_{ist} + \alpha_3 Z_{ist} + \alpha_4 State_s * Year_t + \alpha_i + \alpha_t + \varepsilon_{ist} \quad (1)$$

where Y_{ist} represents the staffing level in nursing home i in state s in year t; $IT_{is,t-1}$ is a one-year lagged binary variable that equals 1 if a nursing home adopts CPOE and 0 otherwise. Hence, the coefficient α_1 captures the effect of CPOE adoption on the dependent variable Y_{ist}. In this two-way fixed-effect model, X is a vector of nursing home characteristics, including the percentage of Medicaid residents, resident health status, and total beds. $Z_{is,t}$ is a vector of market characteristics at the county level, including the intensity of competition as measured by the Herfindahl index, the log of income per capita, and the log of the population. $State_s * Year_t$, a vector of variables, represents state-specific linear trends, which helps to control for the potential unobserved trajectories at the state level. In addition, we control the nursing-home fixed effect (α_i) for time-invariant unobserved factors and the year effect (α_t) for yearly trends. ε is the error term. The standard errors are clustered by nursing home.

5.2 Specification for Heterogeneous Effect

We are most interested in how CPOE adoption differentially affects staffing for nursing homes with different vertical positions. We use the following specification to estimate the differential effects of CPOE adoption on nursing home staffing:

$$Y_{ist} = \beta_0 + \beta_1 IT_{is,t-1} + \beta_2 IT_{is,t-1} * High\ End_{is0} + \beta_3 X_{ist} + \beta_4 Z_{ist} + \beta_5 State_s * Year_t + \beta_i + \beta_t + \varepsilon_{ist} \quad (2)$$

This specification is similar to specification (1). We add in an interaction term by interacting the initial vertical position of each nursing home, *High End*, with its CPOE adoption, *IT*. Note that *High End* is a dummy variable. Therefore, the coefficient β_1 captures the effect of CPOE adoption on staffing for a low-end nursing home with its initial staffing level below median. If $\beta_1 > 0$, this suggests that the adoption of CPOE increases staffing in nursing homes at the low end in a local market. The coefficient β_2 captures the differential effect of CPOE adoption. If $\beta_2 < 0$, this indicates that, in comparison with a nursing home with low vertical position, a nursing home at the high end is associated with a smaller increase or a greater reduction in staffing due to the adoption of CPOE . Hence, $\beta_1 + \beta_2$ captures the CPOE effect on staffing decisions for a nursing home at the high end in a local market.

5.3 Identification Strategy

The econometric challenge in estimating the coefficients of the specifications above is that the adoption of CPOE may be correlated with other (unobserved) decisions related to staffing. For example, the managerial incentives in a nursing home could simultaneously affect decisions about both staffing and the adoption of CPOE. There might be a reverse causality issue as well. For example, nursing homes that intend to increase their staffing level may be more likely to adopt CPOE to maintain their competitiveness.

To establish a causal link between CPOE adoption and the staffing decision in nursing homes, we introduce an instrumental variable approach. Miller and Tucker (2009) show the network effect that greater adoption by other hospitals should lead to greater network benefits for health IT. The network benefits may lead to learning effects (Karshenas and Stoneman 1993) and also reduce the costs of transferring information across the network. As a result, hospitals are responsive to past adoption by other local hospitals. Dranove et al. (2014) suggest that the costs of adopting IT systems depend on the local market for IT services, which is shared by hospitals and nursing homes in the same market. Following these studies, we construct an instrumental variable, *Hospital_CPOE*, measuring the yearly hospital CPOE adoption rates in the local market which is defined by county. We argue this is a valid instrumental variable because nursing homes may share the same network effects or IT resources with hospitals in the local market. However, the adoption behavior of all the hospitals in the local market should not directly affect the quality and staffing decisions of individual nursing homes.

We conduct two tests to bolster the underlying assumption that hospital CPOE adoption is exogenous to nursing home outcomes. First, a range of unobserved local labor market factors could be correlated with local hospital adoption of CPOE and nursing home staffing. To alleviate this concern, we obtained the nurse labor supply and wage information from the CPS data from 2006 to 2012. Table 2 shows the impact of hospital CPOE adoption on the nurse labor market. Columns (1) and (2) show the impact on nurse supply of RN's and LPN's respectively. Nurse supply is measured by the total number of nurse full-time equivalents (FTEs) at the state level divided by state population. Columns (3) and (4) report the results of nurse supply to hospitals identified by industry codes. This helps us see whether there are any shifts in the supply of nurses between acute care and long-term care segments.[22] Columns (5) and (6) show the hospital CPOE effect on the hourly rate for nurses. The columns with odd (even) numbers report the results of RNs (LPNs). Turning to the results, all of these coefficients are small and insignificant after controlling state fixed effects and year fixed effects. There is no evidence indicating that the adoption of CPOE by hospitals changes the labor supply and wages in the licensed nurse markets.

[22] The focus of the jobs between acute care nurses and long-term care nurses differ significantly. Although RNs can work for both hospitals and nursing homes theoretically, the switch between the two healthcare segments is very costly. Nurses have to take additional courses about the skills used in the other segment in order to complete the transition.

Second, we restrict the sample to regions with no change or only one change in hospital adoption from 2006 to 2012. Doing so, we identify 391 counties with one change in hospital CPOE adoption and 486 counties with no changes over the sample period. We define a dummy variable which equals 1 if a county has a large change in hospital CPOE rates since the event year (Year 0) and 0 otherwise. The coefficient is 0.019 with p=0.396, suggesting that the change in hospital CPOE has no effect on nursing home staffing. Then, we replace this dummy variable with a series of dummy variables relative to Year 0, the year in which local hospital CPOE adoption increased. Figure 1 shows the effects of hospital CPOE adoption on nursing home staffing using four or more years before hospital adoption as the base period. All the coefficients are small and insignificant before and after the hospital adopts CPOE, suggesting that staffing in the nursing homes did not change in response to the adoption of CPOE by hospitals. This test also helps alleviate the concern that nursing homes might change their staffing levels in anticipation of the local hospitals' adoption of CPOE.

Further, we empirically test if our instrumental variable satisfies the inclusion restriction using two tests, the results of which are reported in Table 3. First, we check whether the hospital adoption rate, *Hospital_CPOE*, has a weak instrumental variable problem. The Kleibergen-Paap rk Wald F statistic is large (622.17), allowing us to easily reject the null hypothesis of a "weak instrument". Second, in the first-stage regression, we observe the correlation between a nursing home's CPOE adoption decision and local hospitals' CPOE adoption rates is 0.552 at the one percent significance level. This suggests that CPOE adoption decisions in nursing homes are significantly influenced by the adoption decisions made by hospitals in the local markets. We therefore can use the hospital CPOE adoption rates, *Hospital_CPOE*, as the instrumental variable for our key explanatory variable *IT* in both specifications.

6. Empirical Results

In this section, we report our empirical results regarding the impact of CPOE adoption on staffing decisions in nursing homes. We first show the average CPOE effect on nursing home staffing decision. Then, we show how the effect of CPOE adoption on a nursing home depends on the nursing home's vertical position. Consistent with our hypotheses, we find that after the implementation of CPOE, high-end nursing homes reduce staffing while low-end nursing homes increase staffing. This section ends with a series of robustness checks and relevant tests.

6.1 Average Effect

Table 3 reports the impact of the adoption of CPOE on staffing using specification (1). This table covers results using the licensed nurse hours per resident day (LNs HPRD) as the dependent variable. Column (1) reports the OLS results. Column (2) shows the results in the first-stage estimation, followed by

the 2SLS results in Column (3). The OLS coefficient of CPOE in Column (1) is 0.006 and insignificant. After implementing the instrumental variable, the coefficient remains small and insignificant. This finding suggests that there is no significant association between CPOE adoption and average nurse staffing levels.

This set of results is consistent with the results for nurse labor markets in Table 2. The lack of significant results might have contributed to the sparsity of literature about the impact of health IT on labor compared with the rich literature studying the quality implications of health IT.

6.2 Heterogeneous Effects

We further analyze the changes in staffing across nursing homes. We differentiate nursing homes by their initial vertical positions. Table 4 reports the heterogeneous effects of CPOE adoption on staffing, with an emphasis on LNs. The dependent variables are nurse HPRD for LNs and RNs respectively. We report the results using OLS and 2SLS following specification (2) with different measures of vertical position.

The coefficient of CPOE in Column (2) is 0.282 at the one percent significance level, suggesting that nursing homes with the lowest staffing levels in their markets hire more LNs after the adoption of automation technology. The coefficient of the interaction term, *CPOE*Position*, is negative and significant. The coefficient suggests that an increase by one standard deviation in initial staffing distance (*Position*) reduces the staffing increment by 0.170 HPRD compared with the base outcome. When the *Position* is above a certain threshold, the nursing home may use fewer LNs. The overall patterns are consistent with the OLS results in Column (1).

In Column (3), we replace the continuous vertical position measure with a binary variable, *High End*. The positive coefficient of CPOE suggests that low-end nursing homes increase LN staffing by 0.145 HPRD or 7.6% from the mean. The joint F test shows that CPOE adoption reduces the use of LNs by 0.110 HPRD in high-end nursing homes, a 5.8% reduction from the mean.

To show that our results are not sensitive to the choice of minimum staffing ratio, we also use RN minimum staffing ratios as alternative cutoffs for the calculation of vertical position. Although only a few states impose separate mandates for RNs, Harrington (2010) estimated different state standards to a uniform format—RN hours per resident day for a 100-bed nursing home. Columns (4) and (5) report the heterogeneous effects using the estimated RN minimum staffing ratios. The results remain robust both quantitatively and qualitatively.

In general, the results in Table 4 support our hypotheses that low-end nursing homes increase their staff while high-end ones decrease their staff after the implementation of CPOE. As a strategic provider, low-end nursing homes adopting new technologies may invest more in nurses to increase their

competitiveness in the local market, while high-end ones may have incentives to cut staffing in order to contain costs.

6.3 Robustness checks and Relevant Tests

There are many possible reasons for the differences between the OLS and IV results. For example, some omitted variables may be correlated with both CPOE adoption and staffing. Nursing homes may also anticipate the adoption of CPOE and change their staffing levels in advance. In addition, it might be possible that unobservable changes in staffing drivers are associated with CPOE adoption differently across nursing homes with different market positions.

We first examine the timing of the relationship between CPOE adoption and changes in staffing for nursing homes of different vertical positions. To do so, we run our baseline specification using two subsamples, but replace the measure of adoption with dummies for 3 year before adoption, 2 years before adoption, 1 years before adoption, the years of adoption, 1 year after adoption, 2 years after adoption, 3 years after adoption, and 4 or more years after adoption. The base period is four or more years before adoption. Figure 2 shows that prior to CPOE adoption, the LN staffing trends in either high- or low-end nursing homes are relatively stable, as the coefficients are small and insignificant. However, after the initial adoption, the staffing in the low-end nursing homes increases substantially while the staffing demonstrate a weakly decreasing trend in high-end nursing homes. The timing of the impact of CPOE in each subsample suggests that there is not a noticeable trend in an omitted variable driving the estimates for either high-end or low-end nursing homes.

Next, we discuss whether the differential effect of CPOE adoption between the two subsamples could be related to pre-existing difference in trends. F tests show that the difference between one year before adoption and the adoption year across the two groups is very small and insignificant ($p=0.758$). [23] Hence, right before the adoption, there is no statistically significant evidence of different trends for the two groups. With three years back before adoption, however, there does appear to be a pre-trend in the estimated coefficients. We suspect that this might have been driven by unobserved differences between late adopters and others.

To alleviate concerns about possible selection issues, we have included nursing home and year fixed effects and many control variables in the estimation. Nevertheless, we also explore alternative IVs, controls and specifications by running eight robustness checks and several additional tests. Table 5 reports the results of robustness checks.

[23] The p value for the difference between two years before adoption and one year before adoption across the two groups is 0.194.

First, a nursing home's market position may depend heavily on its staffing level relative to other nursing homes within a local market. For example, more residents have private insurance and demand for high quality in high income areas than in low income areas. Their different willingness to pay for quality may affect a nursing home's entry and positioning decisions. In this robustness check, we replace the absolute position measure with a relative position measure within a county. We define a dummy variable that equals 1 if a nursing home's initial position is above county average and equals 0 otherwise. The results in Column (1) show that the CPOE adoption effect on staffing across vertical positions is consistent with our main findings in terms of the sign and significance.

Second, the instrument, *Hospital_CPOE*, relies on variation at the regional level. We are concerned that it might pick up location-specific time-varying unobservables. To alleviate this concern, we obtain the hospital/nursing home affiliation information and construct an alternative instrumental variable that measures the yearly non-affiliated hospital CPOE adoption rates in the local market. In constructing this alternative IV, we exclude the local hospital(s) with which a nursing home is affiliated with and divide the number of non-affiliated hospitals that adopted CPOE by the total number of non-affiliated hospitals in the local market in a given year. Therefore, nursing homes in the same region may have different values of this instrument because of their different affiliation statuses with local hospitals. This IV is positively correlated with the CPOE adoption decision in each nursing home and does not have a weak IV problem (its Kleibergen-Paap rk Wald F statistic is 90.3). Column (2) in Table 5 reports the results using this alternative IV, and the results remain robust.[24]

Third, we replace county with hospital service areas (HSA) or hospital referral region (HRR), and construct instrument variables using the new market definitions respectively. Both IVs are positively associated with nursing home CPOE adoption. The results are reported in Column (3) and (4) of Table 5 respectively. Overall, they are consistent with our theory predictions.

Fourth, certain nurse labor market factors may affect both nursing home CPOE adoption and staffing decisions. To control for that, we add supply and wage information for RNs into the regression. The coefficients in Column (5) show no change in sign and significance, and little change in magnitude.

Fifth, we choose CPOE as the study subject mainly because this is one of the few automation technologies among the major health IT applications. However, nursing homes may also adopt other health IT applications such as a clinical data repository, clinical decision support systems, order entry, or physician documentation at the same time. One may be concerned that CPOE could be a proxy of other health IT

[24] One caveat about this alternative instrument is that the hospital/nursing home affiliation information is a bit noisy (David et al. 2013). We obtained the affiliation information from three sources. The main source was the Hospital Cost Report, which records most of the hospital-based nursing homes in its Sheet S1. The second source is the HIMSS data, which report the parent ID of each nursing home. The third source is the organization name recorded in the OSCAR data. These three sources do not provide consistent information for some nursing homes, so we had to make some assumptions in constructing this alternative instrumental variable.

applications that affect labor. We include the adoption information of the other relevant health IT applications in the specification. If CPOE were merely a proxy for other changes that affect labor, we would expect the results to disappear. The coefficients after controlling other health IT adoption variables (Column 6 of Table 5) show that our main results are robust.

Sixth, 2SLS is a very particular case of a GMM estimator for a particular choice of weighting matrix under conditional homoscedasticity. Baltagi et al. (2000) suggests that the 2SLS estimates might be biased if the homogeneity assumption is not satisfied. To address the concern of possible heteroscedasticity, we conduct a GMM test and report the results in Column (7) of Table 5. The results after relaxing the homogeneity assumption are robust both quantitatively and qualitatively.

Seventh, we show the difference-in-difference results in Column (8) where signs and significance levels of key variables are the same as those in Column 3 of Table 4. Besides, we conduct another robustness check by clustering the standard errors at the county level since the level of variations in the instrumental variable is at the county level in the first stage regression. The results remain robust[25].

We further examine the impact of technology adoption on less-skilled nurse types, CNAs. This evidence should help flesh out the answer to the question posed at the beginning of the paper about how the adoption of automation technology affects the demand for nurses. Table 6 shows that the CNA staffing level decreases by 2.3% in high-end nursing homes but increases by 3.9% in low-end homes after the adoption of automation technology. It seems that the impact of CPOE is relatively smaller on low-skilled types than on high-skilled ones.

7. Extension

Given the significant impact of CPOE on staffing level and the close tie between staffing and quality which naturally affects patient demand, we would like to examine how overall quality and patient admission are affected by CPOE adoption. These tests also shed light on the mechanism of CPOE's impact and further connect the empirical data with our analytical model.

7.1 Effect on Clinical Quality

The impact of CPOE on quality of care offered by medical providers has been widely studied in the literature (e.g., Parente and McCullough 2009). Overall, most of the studies show that quality improves after the implementation of CPOE. Subramania et al. (2007) suggest that CPOE can reduce medical errors and preventable drug-related injuries in the long-term care facilities. We investigate the quality implication of CPOE in the nursing home setting.

[25] The results are available from the authors upon request.

We use the publicly available five-star quality ratings from 2008 to 2012 as our clinical quality measure.[26] After the implementation of the Nursing Home Quality Initiative in 2002, the Center for Medicare and Medicaid (CMS) developed a set of quality indicators to describe the quality of care provided in nursing homes.[27] These measures address a broad range of functioning and health status in multiple care areas and have been validated and endorsed by the National Quality Forum. To improve the information available to consumers, the CMS has constructed the five-star quality ratings based on the scores of this set of quality measures since 2008 (Konetzka et al. 2015).

The five-star quality ratings cover ten dimensions of resident clinical outcomes. The CMS uses a formula to translate the scores for these ten indicators into a risk-adjusted score for each nursing home. Based on the quintile cut points, the CMS assigns stars to different nursing homes. For example, nursing homes whose risk-adjusted scores are above the 80th percentile within each state receive five stars, and those below the 20th percentile get just one star.

We select the quality ratings as the measure of resident clinical outcomes in this study for two reasons. First, the quality ratings are based on the performance of the measures that address residents' functioning and health status in multiple care areas (Werner et al. 2013). Second, and more importantly, this is a risk-adjusted outcome measure, which helps to alleviate the concern that outcome measures are skewed because severely ill residents select good nursing homes. Besides, we acknowledge that changes in resident sorting could affect clinic outcomes, though we have controlled the time-varying resident component measure to alleviate the concern.

Table 7 reports the results regarding the adoption of CPOE and clinical outcomes. Column (1) reports the overall effect on quality ratings using OLS. The coefficient is positive and insignificant. Column (2) shows the first-stage results, suggesting that the IV is highly correlated with the adoption measure. Moreover, this IV does not have the weak IV problem, since the Kleibergen-Paap rk Wald F statistic is 241.20. Column 3 shows that the 2SLS coefficient is 0.198 at the ten percent significance level, suggesting that the adoption of CPOE increases the quality ratings for a nursing home by 6.9%, all else being equal. Overall, the results in Table 7 show that the adoption of CPOE helps to improve residents' clinical outcomes, which is consistent with the prediction of Proposition 2. For high-end nursing homes, the quality improvement may come from the efficiency gain due to the adoption of CPOE and through reduced medical errors. For low-end nursing homes, in addition to the direct benefits of CPOE adoption, the quality also improves thanks to the indirect effect of CPOE adoption: the increase in staffing.

[26] Some observations are dropped when being merged with the available quality rating measure from the CMS.
[27] https://www.cms.gov/Medicare/Provider-Enrollment-and-Certification/CertificationandComplianc/downloads/usersguide.pdf

7.2 Effects on Admissions

We explore two dimensions of demand: quantity and composition. The quantity dimension is measured by total admissions, covering three types of residents: Medicare, Medicaid and private-pay residents. Among these types, both Medicare and private-pay residents are very profitable, and demand for high quality; Medicaid residents are the least profitable, with excess demand. In fact, many Medicaid residents are put on a long waiting list. Based on this institutional background, it would be interesting to see the impact of CPOE adoption on resident composition, which can be measured by total Medicaid admissions.

We obtained the admission measures from SNF cost reports for 2006 to 2012.[28] Since different nursing homes file their cost reports covering different reporting periods, we calculate the daily information for all these variables and take the log transformation of them. Table 8 reports the 2SLS results on demand. Columns (1) and (2) use the log of average daily total admissions as the dependent variable. The results in Column (1) show that there is no significant correlation between CPOE adoption and total admissions, suggesting that overall demand may not change significantly after the implementation of CPOE. This is understandable given that admissions are capped by the number of beds, which cannot be easily changed due to CON laws. This finding also supports our model assumption on fixed total demand. Column (2) shows that there is no significant difference in admission changes for both types of nursing homes.

Columns (3) and (4) use the log of the average daily Medicaid admissions as the dependent variable. The results show that nursing homes that adopted CPOE admitted 14.7% fewer Medicaid residents than those that had not adopted CPOE. This is consistent with the result in Proposition 2 that an increase in automation leads to an increase in average revenue per resident, which is directly related to a decrease in the percentage of Medicaid residents, the least-profitable type. There is no significant difference in changes in Medicaid admissions in terms of vertical position. Table 8 thus delivers an interesting message. The number of Medicaid admissions is negatively associated with CPOE adoption, even though the total admissions remain unchanged. This finding, combined with the results on the quality implication of CPOE adoption, provides further evidence that quality improvement may increase profit margin, supporting our modeling assumption regarding $R(q, \theta)$. These findings also suggest that embracing health IT may be a great opportunity for a facility to improve its vertical position in the local market.

[28] Some nursing homes are hospital-based. Their information is recorded in the Hospital Cost Reports for the SNF units. We obtained the corresponding variables from both cost reports and added a variable indicating the data source (which helps to adjust for possible differences in reporting methods).

8. Conclusion

We study the effect of IT-enabled automation on the staffing decisions of healthcare providers using a unique dataset covering 2,119 surveyed nursing homes in the U.S. over a seven-year period. We find that the adoption of IT-enabled automation technology decreases staffing in high-end nursing homes while increasing staffing in low-end homes. We also find that the adoption of advanced information technology increases the ratings on clinical quality by 6.9% on average, and changes resident composition in the form of a 14.7% decrease in the admissions of Medicaid residents, the least-profitable type, regardless of the nursing home's vertical position.[29] All these results are consistent with the predictions of a theoretical model that incorporates technology adoption and vertical differentiation.

Our findings suggest that the relation between staffing and automation adoption is mixed. It crucially depends on the relative strength of the two opposing effects, complementarity and substitution, in different types of nursing homes. Our theoretical model indicates that the complementarity effect dominates the substitution effect in low-end nursing homes. To increase their competitiveness in the local marketplace and attract lucrative residents, such nursing homes have greater incentives to hire nurses after they adopt the automation technology. By contrast, the substitution effect dominates the complementarity effect in high-end nursing homes. Since automation technology significantly increases the utilization of nurse time but the marginal benefit of providing additional quality is relatively low, these high-end nursing homes are likely to reduce their staffing to contain costs. These insights complement the current understanding of the impacts of information technology on labor from the macroeconomic perspective.

The fact that the average effect of the adoption of a health IT system on nursing home staffing is not statistically different from zero while the analysis through the perspective of vertical position reveals a very different and much richer story demonstrates the importance of using the right "microscope" to dissect the data. In particular, our research suggests that an organization's vertical position is potentially important when studying the implications of IT for labor decisions.

One potential limitation of our study is the use of the HIMSS data, which cover a small set of nursing homes. Although nursing homes in the HIMSS sample share similar occupancy rates and resident profiles with the entire nursing home population, surveying a broader set of nursing homes may be helpful for other IT-related nursing home research.

Our findings have important implications. For individual nurses, automation technology does not necessarily result in reduced job opportunities. Nurses can anticipate their prospective employment status by recognizing the vertical position of the nursing home where they are working or will work. For a nursing home, the effect of technology adoption on staffing decisions largely depends on its vertical position in the

[29] Our data shows that the overall percentage of Medicaid residents increases over the sample period. Combined with our results, it seems that some Medicaid residents may have shifted to non-CPOE nursing homes.

marketplace. When IT adoption becomes the new trend, managers can follow either a revenue expansion strategy or a cost reduction strategy depending on the nursing home's vertical position. We believe that these managerial implications can be generalized to other labor-intensive industries such as day care and education where quality is positively correlated to staffs serving customers. However, one should be cautious and not over-generalize our findings to industries in which vertical positioning might be less likely to be connected with labor. For policy makers, our results show that adoption of health IT improves quality in the nursing home industry, so the government should provide subsidies to nursing homes to encourage adoption.

Future work along this research line can consider two important questions. One is the interoperability issues of CPOE. Recently, the Office of the National Coordinator for Health Information Technology (ONC) asked health facilities to meet the standards and obtain ONC certification. How should different organizations share records? What are the unexpected consequences of sharing medical records? These are important research topics. The other is to separate the IT vintage effect from the process learning effect of health IT on productivity. This requires more detailed data sets, structural models or other new identification strategies.

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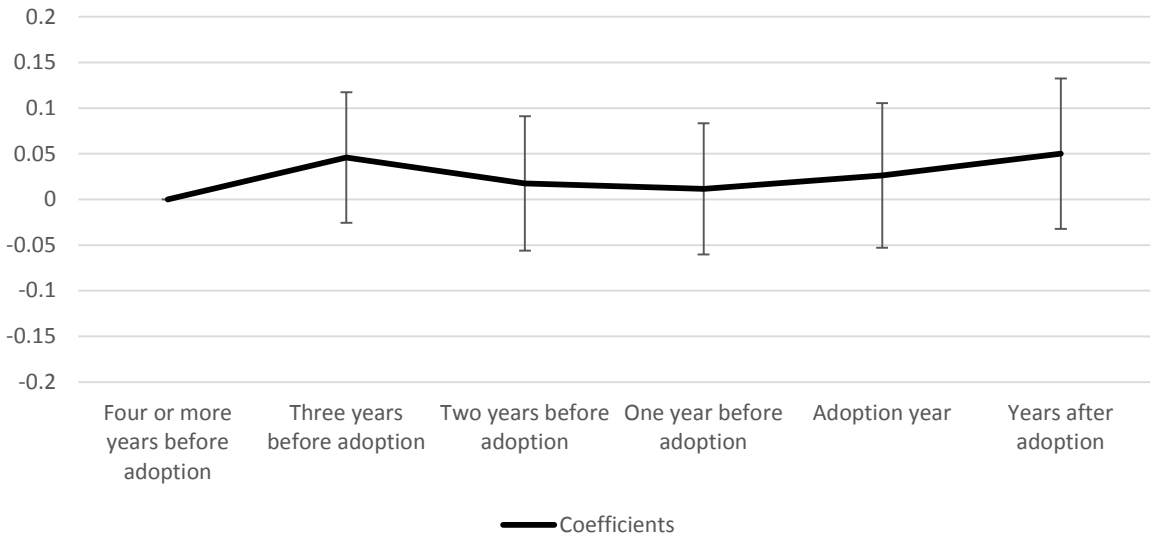
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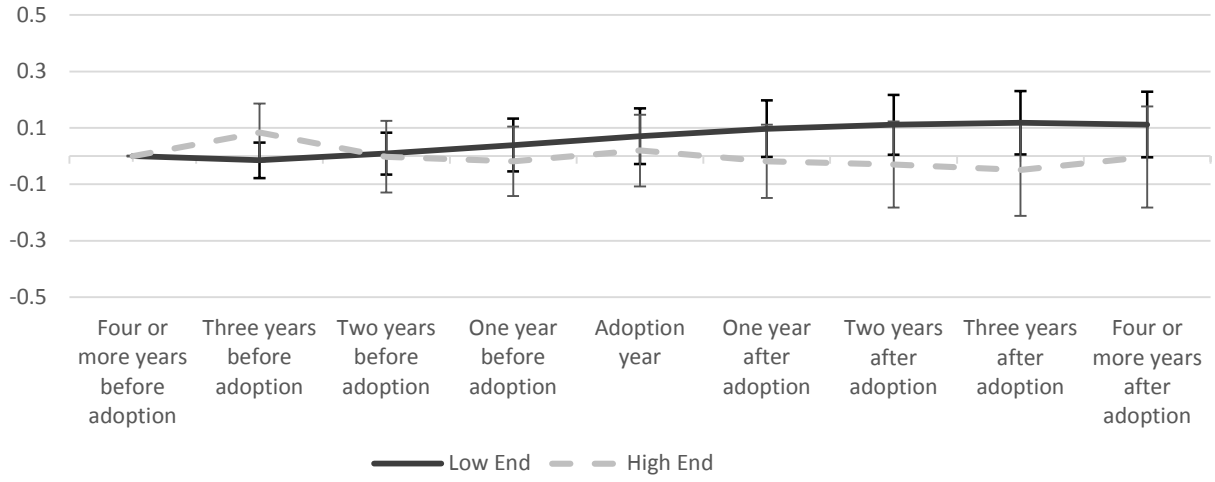
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Figure 1: The Impact of Hospital CPOE Adoption on Nursing Home Staffing



Notes: The base period is four or more years before hospital CPOE adoption. Error bars show 95 percent confidence intervals.

Figure 2: Coefficients by Years from Nursing Home CPOE Adoption



Notes: The base period is four or more years before nursing home CPOE adoption. Error bars show 95 percent confidence intervals.

Table 1: Summary Statistics

Variable	Mean	SD	Definition
Technology Adoption			
CPOE	0.20	0.40	1 if CPOE was adopted last year
Hospital_CPOE	0.24	0.31	hospital CPOE adoption rates last year
Staffing Measures			
LN HPRD	1.91	0.97	licensed nurse hours per resident day
RN HPRD	1.00	0.74	registered nurse hours per resident day
Vertical Position			
Position	1.42	0.99	initial distance from the minimum staffing requirement
High End	0.47	0.50	1 if the position is above median
Control Variables			
Percentage of Medicaid	0.55	0.27	percentage of Medicaid patients
Beds	100.70	79.30	total beds (weighted by 100 in regressions)
ADL Index	8.21	3.68	ADL index describing patient health status
HHI Competition	0.03	0.03	competition measure at the county level
Log Income	10.46	0.57	log of income per capita at the county level
Log Elderly Population	9.76	1.67	log of the elderly population at the county level

* Number of observations is 12,313. Unit of observation is nursing home/year.

Table 2: The Impact of Hospital CPOE on Nurse Labor Market

Dependent Variable	State Nurse Supply		State Hospital Nurse Supply		Wage: Hourly Rate (cent)	
Nurse Type	RNs	LPNs	RNs	LPNs	RNs	LPNs
	(1)	(2)	(3)	(4)	(5)	(6)
Hospital_CPOE	-0.001	-0.0002	-0.002	-0.00001	-200.881	-531.14
	(0.001)	(0.001)	(0.001)	(0.001)	(141.867)	(381.591)
State Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	357	354	357	354	356	355
R-squared	0.089	0.026	0.095	0.028	0.279	0.082

Robust standard errors in parentheses are clustered by state

*** p<0.01, ** p<0.05, * p<0.1

Table 3: The Average Effects of Nursing Home CPOE Adoption on Staffing

Dependent Variable:	Average Effect		
LN HPRD	OLS	First Stage	2SLS
	(1)	(2)	(3)
CPOE	0.006		-0.001
	(0.019)		(0.039)
IV: Hospital_CPOE		0.552***	
		(0.022)	
Nursing Home Dummies	Y	Y	Y
Year Dummies	Y	Y	Y
Individual State Linear Trends	Y	Y	Y
Time-varying Controls	Y	Y	Y
Weak Identification Test	Kleibergen-Paap rk Wald F statistic: 622.17***		
Observations	12313	12313	12250
Within R-squared	0.044	0.272	0.044
Number of Providers	2119	2119	2056

Robust standard errors in parentheses clustered by nursing home
Time-varying controls include Percentage of Medicaid, Beds, ADL Index, HHI, Log Income and Log Elderly Population.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Heterogeneous Effects of Nursing Home CPOE Adoption on Staffing

Dependent Variable:	Licensed Nurses			Registered Nurses	
Hours per Resident Day	Minimum LNs			Minimum RNs	
	OLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
CPOE	0.106***	0.282***	0.145***	0.154***	0.073**
	(0.036)	(0.062)	(0.046)	(0.040)	(0.029)
CPOE * Position	-0.065**	-0.172***		-0.145***	
	(0.029)	(0.042)		(0.044)	
CPOE * High End			-0.255***		-0.109**
			(0.071)		(0.047)
F test: CPOE+CPOE* High End			-0.110**		-0.036*
Nursing Home Dummies	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
State Linear Trends	Y	Y	Y	Y	Y
Time-Varying Controls	Y	Y	Y	Y	Y
Observations	12,313	12,250	12,250	12,250	12,250
Within R-squared	0.046	0.040	0.041	0.057	0.058
Number of Providers	2,119	2,056	2,056	2,056	2,056

Robust standard errors in parentheses clustered by nursing home
Time-varying controls include Percentage of Medicaid, Beds, ADL Index, HHI, Log Income and Log Elderly Population.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Robustness Checks

Dependent Variable:	Alternative Measures, Controls and Specifications							
LN HPRD	Relative Position	IV NH	IV HSA	IV HRR	Control supply/wage	Control other IT Apps	GMM	Diff-in-Diff (OLS)
(2SLS)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CPOE	0.221***	0.127*	0.103**	0.216**	0.146***	0.147***	0.146***	0.049***
	(0.070)	(0.072)	(0.044)	(0.110)	(0.046)	(0.050)	(0.046)	(0.017)
CPOE * High End	-0.258***	-0.393***	-0.183***	-0.443***	-0.257***	-0.251***	-0.255***	-0.082**
	(0.078)	(0.116)	(0.063)	(0.149)	(0.071)	(0.071)	(0.072)	(0.037)
Time-Varying Controls	Y	Y	Y	Y	Y	Y	Y	Y
Nursing Home Dummies	Y	Y	Y	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y	Y	Y	Y
State Linear Trends	Y	Y	Y	Y	Y	Y	Y	Y
Observations	12,250	12,408	10,448	10,459	12,237	12,237	12,067	12,313
Within R-squared	0.041	0.032	0.04	0.026	0.041	0.042	0.041	0.044
Number of Providers	2,056	2,061	1,995	1,997	2,056	2,056	2,041	2,119

Robust standard errors in parentheses clustered by nursing home

Time-varying controls include Percentage of Medicaid, Beds, ADL Index, HHI, Log Income and Log Elderly Population.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effects of Nursing Home CPOE Adoption on CNA Staffing

Dependent Variable: Hours per Resident Day	Certified Nurse Aids (CNAs)			
	OLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
CPOE	-0.012	0.026	0.150**	0.105**
	(0.023)	(0.019)	(0.062)	(0.051)
CPOE * Position			-0.085**	
			(0.036)	
CPOE * High End				-0.166**
				(0.067)
Nursing Home Dummies	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y
State Linear Trends	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y
Observations	12,313	12,250	12,250	12,250
Within R-squared	0.021	0.021	0.019	0.020
Number of Providers	2,119	2,056	2,056	2,056

Robust standard errors in parentheses clustered by nursing home
Time-varying controls include Percentage of Medicaid, Beds, ADL Index, HHI, Log Income and Log Elderly Population.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Effects of Nursing Home CPOE Adoption on Clinical Quality

Dependent Variable: Clinical Quality	Five Star Ratings		
	Ratings on Quality Measures		
	OLS	First Stage	2SLS
	(1)	(2)	(3)
CPOE	0.008		0.198*
	(0.046)		(0.102)
IV: Hospital_CPOE		0.540***	
		(0.025)	
Nursing Home Dummies	Y	Y	Y
Year Dummies	Y	Y	Y
Individual State Linear Trends	Y	Y	Y
Time Varying Controls	Y	Y	Y
Weak Identification Test	Kleibergen-Paap rk Wald F statistic: 241.20***		
Observations	8,634	8,632	8,489
Within R-squared	0.057	0.28	0.054
Number of Providers	2,004	2002	1,859

Robust standard errors in parentheses clustered by nursing home
Time-varying controls includes Percentage of Medicaid, Beds, ADL Index, HHI, Log Income and Log Elderly Population.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Effects of Nursing Home CPOE Adoption on Total Admissions and Medicaid Residents

Dependent Variable:	Resident Composition			
Log of Daily Admissions	Total Admission		Medicaid Admission	
(2SLS)	(1)	(2)	(3)	(4)
CPOE	0.006	0.138	-0.147**	-0.201*
	(0.086)	(0.147)	(0.072)	(0.112)
CPOE * Position		(0.079)		0.038
		(0.057)		(0.052)
Nursing Home Dummies	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y
State Linear Trends	Y	Y	Y	Y
Time Varying Controls	Y	Y	Y	Y
Observations	11,017	11,017	9,548	9,548
Centered R-squared	0.282	0.282	0.055	0.054
Number of Providers	1,880	1,880	1,630	1,630

Robust standard errors in parentheses clustered by nursing home

Time-varying controls include Percentage of Medicaid, Beds, ADL Index, HHI, Log Income and Log Elderly Population.

*** p<0.01, ** p<0.05, * p<0.1