THE DETERMINANTS AND IMPLICATIONS OF FIRMS' WORKFORCE CONFIGURATION: THE CASE OF HOME HEALTH

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Dedicated to my father Hyungbyung

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ABSTRACT

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A fundamental challenge for labor-intensive firms facing demand uncertainty is how to configure their workforce to improve quality and performance. This dissertation investigates determinants of firms' workforce configuration, with a focus on the mix of temporary and permanent nurses, and its implications on patient outcomes, a central measure of performance in health care. This is a timely topic since many industries including health care are increasingly using alternative work arrangements. This dissertation uses novel and rich proprietary data from a large US freestanding home health company. The data provide detailed information on both the consumption and production sides of home health care delivery: utilization, referral sources, risk factors and health outcomes of patients as well as nurses' work logs and human resources characteristics. In Chapter 1, I investigate the effect of firms' labor mix on patient readmission, a main quality marker in post-acute care, using exogenous variation in full-time nurses' activeness in the patient's neighborhood and unavailability of nearest full-time nurses. I find that patients who received one standard-deviation higher proportion of full-time nurse visits were 7 percent less likely to be readmitted. In Chapter 2, I investigate the effect of reputation on firms' labor mix strategy under demand uncertainty. Firms face a trade-off in using temporary nurses: they provide flexibility in responding to demand fluctuations but may impede the establishment of reputation through lower quality of service. I present and test a model of firm's labor mix choices where the labor mix dynamically shapes the market's perception of the firm's quality (i.e. reputation), and the firm's demand is in turn stochastically linked to its reputation. I find evidence consistent with the model: firms with lower reputation, especially young firms, increased

the percentage of full-time nurses with demand volatility. Young firms trade off short-term profitability for long-term reputation gains. In Chapter 3, I investigate the effect of firms' workforce assignment on readmission through care discontinuity or handoffs. Using exogenous variation in workflow interruption caused by providers' inactivity, I find handoffs to increase the likelihood of readmission. One in four readmissions during home health would be avoided if handoffs were eliminated.

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1.1. Introduction

An increasing number of firms in the US hire workers in alternative work arrangements, defined as temporary help agency, on-call, contract company, and independently contracted or freelancing workers (Katz and Krueger, 2016). Between 2005 and 2015, the percentage of workers in those arrangements rose from 10.7 percent to 15.8 percent, and 94 percent of the net employment growth in the US economy during this period is estimated to have occurred in alternative work arrangements (Katz and Krueger, 2016). Health care, in particular, is one of the fastest growing industry groups with a 53-percent growth in the percentage of health care professionals in alternative work arrangements between 2005 and 2015 and a 74-percent growth between 1995 and 2015 (Katz and Krueger, 2016).[1] This trend of an increasing use of workers in alternative arrangements in health care naturally raises the question of whether using more of these workers has any impact on patient health outcomes, a central measure of performance in health care.

Key problems in estimating the impact of using alternative work arrangements on health outcomes are attribution and selective assignment. A multitude of other organizational factors, such as facility resources or technology tools, simultaneously influence the patient experience and health outcomes. Provider organizations with more resources may adopt staffing practices—such as hiring more professionals in permanent work arrangements or providing better work environments—that achieve favorable health outcomes (Aiken et al., 2007). Moreover, providers may selectively assign patients to professionals in different work arrangements: for example, relatively healthier patients are matched with professionals in alternative work arrangements.

[1] The percentage of health care professionals in alternative work arrangements was 5.3 percent, 6 percent, and 9.2 percent in 1995, 2005, and 2015, respectively. *Health care professionals* refers to workers in the *Healthcare Practitioners and Technical Occupations* and *Healthcare Support Occupations* groups, as defined by the Bureau of Labor Services. The former group includes physicians and nurses while the latter includes physician aides and nurse aides.

In this chapter, I use a novel and rich dataset on home health and develop an empirical framework that allows me to overcome these inference challenges. First, I use novel proprietary data on home health care utilization in which patients are isolated in their homes and thus their health outcomes are unlikely to be confounded by other facility resources. Second, I use a plausibly exogenous variation in patient assignment to different types of nurses using permanent nurses' activeness in the patient's area.

There are different work arrangements used for both permanent and temporary workforces, respectively, in home health. Thus, to investigate whether permanent and temporary nurses yield a systematically different patient outcome, I estimate whether receiving more care from full-time nurses leads to a different likelihood of hospital readmission.

My identification strategy is to exploit the variation in full-time nurses' activeness across ZIP codes and care timings. When a patient happened to live in a ZIP code or start home health care at a time that her firm used more full-time nurses, she would receive more full-time nurse visits. The patient's location and timing of care are potentially exogenous with respect to the patient's likelihood of readmission.

For this analysis, I use proprietary home health data and construct patient-episode level data for a set of elderly patients who had a hospitalization prior to home health care during the years 2012–2015. I use a two-stage least squares (2SLS) estimation using the instrumental variable discussed above. My findings are twofold. First, patients who lived in ZIP codes where full-time nurses were more active at the start of care indeed had a higher proportion of full-time nurse visits. Second, patients who received a higher proportion of full-time nurse visits were less likely to be readmitted to a hospital. One-standard-deviation increase in the proportion of full-time nurse visits (0.41)—equivalent to about two more full-time nurse visits out of 6 in total—was associated with a 7-percent decrease in the likelihood of readmission compared to the mean. This effect holds after controlling for patients' underlying health characteristics, office-level demand and labor supply characteristics, patients' ZIP code fixed effects, firm fixed effects, month fixed effects, and fixed effects related to the timings of the start and end of care. Moreover, this estimated effect is conservative since when full-time nurses were active, firms tended to have sicker patients by several severity measures.

Previous literature has examined the effect of workers in alternative work arrangements on performance but there is a lack of consensus (Bae et al., 2010; Xue et al., 2012; Lotti and Viviano, 2012; Aiken et al., 2013; Figlio et al., 2015; Lasater et al., 2015; Hockenberry and Becker, 2016; Lu and Lu, 2016). On the one hand, Figlio et al. (2015) find in the university setting that students learned relatively more from contingent faculty in the first-term courses after controlling for student fixed effects and next-class-taken fixed effects, compared to tenure-track or tenured professors. In the hospital setting, Xue et al. (2012) and Aiken et al. (2013) find no statistically significant difference in mortality in hospital units run by a higher share of supplemental registered nurses (RNs). Aiken et al. (2007) similarly find that supplemental nurses were not associated with poor patient outcomes after controlling for the quality of work environments. Lasater et al. (2015) find a greater use of supplemental RNs to have no statistically significant association with patient satisfactions measured by whether patients would recommend their hospital. On the other hand, Hockenberry and Becker (2016) find that 10 dimensions of patient satisfaction scores were lower in hospitals with a higher proportion of contract nurse hours, even for patient satisfaction data coming from the same source as Lasater et al. (2015). Bae et al. (2010) find the positive association between the level of external temporary RN hours and several poor patient safety outcomes, such as patient back injuries and falls, in hospitals. Pham et al. (2011) find that temporary staff, including physicians and nurses, was associated with more harmful medication errors in emergency departments. Lu and Lu (2016) also find greater service quality deficiency citations in nursing homes employing greater RN contract hours as a proportion of total resident days. Lotti and Viviano (2012) find that reforms incentivizing the use of permanent labor were associated with higher total factor productivity in Italian manufacturing firms.

The principal contribution of this chapter is to overcome weaknesses in the prior literature by accounting for the non-random matching of providers in different work arrangements with patients. I demonstrate that accounting for this endogeneity is important as the OLS effects of the proportion of full-time nurse visits are not statistically significant whereas the 2SLS effects are statistically significant and greater in magnitude. To the best of my knowledge, this chapter is the first to use an econometric method to overcome the inference problem. Broadly, the chapter is related to the literature on the relationship between staffing and quality (Needleman et al., 2011; Tong, 2011; Cook et al., 2012; Mark et al., 2013; Lin, 2014; Matsudaira, 2014).

The remainder of this chapter is organized as follows. In Section 1.2, I provide brief background on home health care to provide necessary institutional details to understand my empirical strategy. In Section 1.3, I describe the data and sample restriction rules. In Section 1.4, I describe the key inference problems in estimating the effect of the proportion of full-time nurse visits on patient readmission. In Section 1.5, I discuss the empirical strategy. In Section 1.6, I present the estimation results. In Section 1.7, I conclude the chapter.

1.2. Background

Home health care, which is provided to homebound patients who need skilled nursing or therapy services, is an important and rapidly growing segment of the post-acute care delivery system. Home health care is composed of largely six service disciplines in which home health firms demand labor: skilled nursing, home health or personal care aid, physical therapy, speech-language pathology, occupational therapy, and medical social services.[2] I provide a detailed background on the home health care industry and the workforce distribution across disciplines in Appendices A.1 and A.2, respectively, at the end of the dissertation.

In this chapter, I focus on the skilled nursing workforce—the combination of registered nurses (RNs) and licensed practice nurses (LPNs)—since nurses provide the medical service most relevant to potentially determining hospital readmissions and since their visits account

[2] Medicare covers only these six discipilnes.

for the majority of overall home health visits. Thus, among the six service disciplines, home health firms' demand for skilled nurses is the highest and they maintain the largest capacity of them each week.

Nurses are hired under largely two compensation schemes: salary with guaranteed work and expected number of visits for each week and piece-rate pays with no guaranteed work and visit-based hiring. Thus, one can think of salaried nurses as "permanent" and piece-rate paid as "temporary" workers in this chapter. Under salary, nurses can be hired either on a full-time, part-time with benefits, or part-time without benefits basis, or for managerial or administrative positions. Full-time nurses are the primary salaried work arrangement, comprising 40 percent of a firm's workforce every week on average. Under piece-rate pay, nurses can be hired either on an on-call basis directly by the firms or hired as contractors through temporary help agencies. On-call nurses are the primary piece-rate paid work arrangement, comprising more than 30 percent of a firm's workforce every week on average.

1.2.1. Differences between Permanent and Temporary nurses: Descriptive Statistics

A lack of consensus in the previous literature on the effect of alternative work arrangements on quality and performance may reflect the fact that the effect plausibly varies across settings. However, theoretically there are opposing directions through which workers in alternative work arrangements can affect performance. On the one hand, lower-quality workers may be more likely to sort into alternative work arrangements if firms have lower standards of hiring for those arrangements. Once employed by a firm, workers hired in alternative work arrangements may also have shorter engagement with the firm and lack opportunities to develop firm-specific skills (Broschak and Davis-Blake, 2006; Cuyper et al., 2008) or receive support from colleagues (Witte and Nswall, 2003). Negative worker outcomes for workers in alternative work arrangements, such as lower wages or lower benefits, could reduce their morale and productivity (Harley, 1994; Hockenberry and Becker, 2016).

On the other hand, using workers in alternative work arrangements could have a positive effect on performance if they provide supplementary labor to address a shortage or high workload of regular workers. Flexible staffing strategies could offset the negative effects of low staffing or high workload per worker which have been consistently noted by previous literature (Aiken et al., 2010; Kuntz et al., 2014; Berry Jaeker and Tucker, 2016). Moreover, to the extent that alternative work arrangements are used as a screening device or stepping stones for more permanent positions, the former do not necessarily attract less competent nurses (Booth et al., 2002). However, this case is unlikely in in my data since it is rare for permanent nurses to be hired first in temporary work arrangements and for temporary nurses to change into permanent positions.

Before examining the effect of the proportion of full-time nurse visits on patient readmission, I explore whether full-time nurses are different from nurses hired in other work arrangements. If there is no meaningful difference, there is no reason for firms to differentially treat them and expect any difference in the quality of care. In Table 1, I report mean values of key labor supply and pay characteristics of nurses in each work arrangement. I focus on the comparison of full-time and on-call nurses, who represent the majority of salaried and piece-rate paid workforce.

Full-time nurses had substantially higher workloads, as measured in terms of number of visits. Panel A shows that conditional on providing at least one visit, full-time nurses provided 22 visits per week on average compared to on-call nurses who provided 9 visits per week. However, the average length of visits provided by full-time nurses was at 46 minutes shorter by 4 minutes than that of on-call nurses. Reflecting the difference in workloads, full-time nurses were paid slightly less than 3 times the total weekly pay of on-call nurses, as shown in Panel B. However, on the per-visit rate, full-time nurses get paid less than on-call nurses by $12 on average, which may be a compensating differential for benefits. Moreover, full-time nurses' average length of employment of 21 months was 5 months longer than that of on-call nurses.[3]

[3] To obtain these statistics, I restricted to nurses who terminated their employment, where the termination was defined as either permanently exiting the workforce or providing no visits for more than 90 consecutive

Another qualitative difference between salaried and piece-rate paid nurses lies in the amount of training and attendance of case review conferences. Data on these aspects are unavailable. However, according to interviews with administrators in the company which provided me with the data, salaried nurses must receive training at the start of employment and get additional training regularly. They also spend more time in the firm offices and attend conferences with other care team members to review patient cases. On the other hand, piece-rate paid nurses are not obliged to receive training at the start of employment and do not typically receive additional training afterwards. They also do not usually attend conferences for case reviews.

Table 1 alone cannot entirely explain why a higher proportion of full-time nurse visits would improve patient outcome (i.e. reduce hospital readmission). However, data suggest that full-time nurses accumulate much more experience by providing more visits as well as staying employed for longer. To the extent that the experience has a positive correlation with performance—whether it is due to the vintage effect or selection (Murnane and Phillips, 1981) or learning by doing (David and Brachet, 2009)—full-time nurses may provide higher quality of care.[4] The same effect is predicted to the extent that full-time nurses develop greater expertise and superior knowledge of firms' culture and standards by spending more time at firms' offices and with colleagues. These forces, however, might be counterbalanced with factors such as shorter visit lengths or higher workloads (Brachet et al., 2012), which could produce a positive effect of proportion of full-time nurse visits on hospital readmission.

1.2.2. Firms' Assignment of Temporary and Permanent Nurses to Patients

Why do some patients receive more full-time nurse visits than others? Before investigating the impact of receiving more full-time nurse visits on readmission, I describe firms' practice of assigning nurses to patients, which drives the variation in the proportion of full-time nurse

days.

[4] Medoff and Abraham (1980) find no correlation between experience and relative rated performance though they find a strong correlation between experience and relative earnings among managerial and professional employees within the same grade level.

visits across patients. Home health firms' assignment of nurses to patients is based largely on matching by distance as it involves mobile workforces.[5] Since many nurses commute from home directly to patients' homes, firms try to assign to a patient the nurses who live close by to her in order to minimize nurses' travel time and costs. Travel time has the potential to affect not only directly firms' mileage payment to nurses but also indirectly employee retention (Chapple, 2001) and labor supply (Gutiérrez-i Puigarnau and van Ommeren, 2010; Gimenez-Nadal et al., 2011). This is despite the possibility that a nurse may incur one-time costs of traveling to and from a remote area at the beginning and end of the day and mostly travel short distances between different patients' homes located near each other during the day.

In my data, for a given patient, nurses who actually visited the patient lived closer to her than other nurses who were active but did not visit her. Nurses who actually visited the patient lived 11 miles away whereas those who did not visit her lived 14 miles away.[6] The mean difference of 3 miles within the patient is not only economically significant but also statistically significant at the one percent level according to the paired t-test.

While matching of nurses with patients is largely based on distance, a majority of patient's care is provided by full-time nurses. On average, a patient receives 6 nurse visits in total. Approximately 60 percent of them are provided by full-time nurses; 8 percent by part-time with benefits nurses; 6 percent by part-time with benefits nurses; 17 percent by on-call nurses; 0.3 percent by contractor nurses; and 8 percent by office or other nurses. Figure 1 shows the variation in the proportion of full-time nurse visits across patient episodes. A large number of patients receive either zero or only full-time nurse visits. 24 percent of the

[5]The geography-based assignment of service providers to patients has been well noted in the home health care settings as well as in other mobile workforce settings, such as police. The operations management literature has long addressed this "districting" problem of how to partition a firm's service market region into a contiguous set of districts and assign workers to each district to minimize each worker's travel distances and equalize the workload across workers (Tavares-Pereira et al., 2007).

[6]To analyze this, for each patient, I divide nurses who were active during months of the patient's care into two groups by whether they actually visited her. Within the patient, I compute the mean distance to the nurses in each group at the 5-digit ZIP-code level, the finest level of geography I can obtain for the patients' and nurses' home addresses.

patients receive zero full-time nurse visits, and 36 percent of patients receive only full-time nurse visits. The remaining 40 percent receive a mix of full-time nurse and other nurse visits, with the median proportion of full-time nurse visits being 0.75.

1.3. Data

I use rich and novel data from a large US for-profit freestanding home health provider firm operating 106 autonomous offices in 18 states during January 2012 through August 2015.[7][8] These data provide information for each patient including underlying risk factors and outcomes at an unusual level of detail since the Center for Medicare and Medicaid Services (CMS) requires each office to collect extensive demographic and health risks data using the CMS's Outcome and Assessment Information Set (OASIS) surveys.[9] The patient data contain a rich set of underlying health risks assessed at the beginning of each home health admission and hospital readmission outcomes.[10] I focus on hospital readmissions as a key measure of quality of care since both hospitals and freestanding HHAs view it as a key competitive differentiator among HHAs under the Hospital Readmissions Reduction Program (HRRP) established by the Affordable Care Act (ACA) (Worth, 2014).

These data contain the entire home health visit records in each office showing all the interactions between a patient and individual providers who served her. I match these visit-level data with the human resources data containing the history of employment arrangements for each provider to measure the proportion of visits provided by nurses in each work ar-

[7]These 18 states are Arizona, Colorado, Connecticut, Delaware, Florida, Hawaii, Massachusetts, Maryland, North Carolina, New Jersey, New Mexico, Ohio, Oklahoma, Pennsylvania, Rhode Island, Texas, Virgina, and Vermont.

[8]This large set of independently run offices alleviates some concern about the generalizability of our results to other HHAs even if they all belong to one company. During 2013, compared to a national sample of freestanding agencies, home health offices in our sample tend to be larger, have a lower share of visits provided for skilled nursing and instead have a higher share of visits provided for therapy, and have a lower share of episodes provided to dual-eligible Medicare or Medicaid beneficiaries, which seem to be more common characteristics of proprietary agencies (Cabin et al., 2014; MedPAC, 2016a).

[9]These patients include all the patients enrolled in both public and private versions of Medicare, Medicaid and a small fraction of private insured patients for which their plans required the collection of OASIS data.

[10]The OASIS data actually contain two variables which I use to identify whether a patient had a hospital readmission: whether patients had a hospitalization prior to home health care and hospitalization dates during home health care.

rangement during each patient's care. Using these visit-level data, I can also construct the firm-day level data showing office's demand and labor supply conditions. I use this dataset to construct the mean level of ongoing home health care episodes and active nurses, and the mean proportion of nurses in each work arrangement during each patient's care.

Finally, my data provide 5-digit ZIP code level home addresses for both patients and nurses. It is rare to have home addresses for nurses in health care data, which offers a unique opportunity to construct an instrument based on the distance between patient and nurse's homes as described in Section **??**.

I construct the sample at the patient episode level, where an episode is defined as a 60-day period of receiving home health services.[11] Each patient episode is handled by a single office. Since each office autonomously decides scheduling and staffing and is run as a profit center, I regard each office as a separate "firm" in my empirical analysis. In my sample, I exclude firms that are senior living offices whose primary clientele is residents of senior living facilities since these firms pursue a different workforce configuration strategy than firms that focus on home health care. I also exclude firms serving fewer than 50 episodes in a ZIP code for stable estimation. Furthermore, I restrict to the set of patients who received a single episode of home health care since patients receiving multiple episodes likely face a different distribution of labor mix. I also exclude patients who received only one nurse visit since they cannot experience a mix of nurses in different work arrangements. I exclude outlier patients who received greater than 99th percentile (18) of the number of nurse visits during care. Thus, my final sample used for the analysis contains 21,200 patient episodes that live in 203 ZIP codes and are served by 39 firms operating in 10 states.

[11] This definition of a 60-day home health episode is based on the fact that the Center for Medicare and Medicaid Services (CMS) pays a prospective payment rate for each episode to home health agencies for "traditional Medicare" (Part A) enrollees, not privately insured Medicare enrollees. A patient can have multiple episodes during a home health care admission.

1.4. Inference Problem

Estimating the effect of the proportion of full-time nurse visits on patient readmission is challenging for several reasons. The first and central problem is that firms' assignment of full-time nurses to patients may depend on patients' severity. Sicker patients are more likely to be assigned full-time nurses because those nurses can provide more continuous care or have more experience due to longer tenure. Section 1.2.1 shows that full-time nurses work more per week and work longer. To the extent that patients who are sicker in unobserved dimensions have a higher proportion of full-time nurse visits, estimating an OLS effect of such a proportion on the patient readmission would result in an upward bias and work against finding a negative effect.

Indeed patients who received a higher proportion of full-time nurse visits appear to be sicker according to many observed characteristics. Table 2 shows the mean values for several patient characteristics for four different groups of patients based on the proportion of full-time nurse visits: 1) zero; 2) greater than zero and less than median (0.75); 3) equal to or greater than median and less than one; and 4) one. Overall, Group 1 patients who received zero full-time nurse visits were most saliently healthier than Groups 2–4 of patients who had at least one full-time nurse visit during care. Panel B shows that Group 1 had a low risk for hospitalization: these patients had few past hospitalizations, did not show mental decline, and took few medications. In Panel C, Group 1 was older but more likely to be white and enrolled in Medicare Advantage, both of which have been shown to be associated with better health (Kawachi et al., 2005; Brown et al., 2014). In Panel D, Group 1 had a lower Charlson comorbidity index and was less likely to report severe overall status and have severe pre-home health care conditions.

One can observe a similar gradient of severity across Groups 2–4. Groups 3–4 patients who had at least 75 percent of full-time nurse visits appeared similar, and Group 3 was even sicker than Group 4 on some measures. However, both of these groups tended to be sicker than Group 2 in many characteristics. In our estimation framework, we control for all of these observed patient severity characteristics. However, to the extent that these observed characteristics are correlated with unobserved characteristics, such as dynamic progression of severity during patient's care, the effect of full-time nurse visits on patient readmission cannot be identified. To address this problem, I use an instrument variables approach, which I describe in detail in Section 1.5. This approach relies on activeness of full-time nurses in the patient's local area and the number of nearest full-time nurses who did not visit the patient as an exogenous source of variation.

1.5. Empirical Strategy

To address the inference problem described in Section 1.4, I use an instrumental variables method to estimate the labor mix on hospital readmission.[12] I use the activeness of full-time nurses in the patient's ZIP code at the start of care, which yields a plausibly exogenous variation in the labor mix. I describe this instrument in detail below.

1.5.1. Activeness of Full-Time Nurses

A single firm typically serves multiple ZIP codes, and naturally, there is a variation in the activeness of full-time nurses across ZIP codes. If a new patient needing home health care happens to live in a ZIP code where full-time nurses are originally active, then she would receive a higher fraction of full-time nurse visits. Therefore, the activeness of full-time nurses in the patient's ZIP code must have a strong positive correlation with her fraction of full-time nurse visits.

To construct the instrument variable measuring the activeness of full-time nurses for each patient episode i, I use the share of total nurse visits in i's ZIP code that are provided by full-time nurses hired by i's firm at i's start of care. For each i, let $f(i)$, $z(i)$, and $m(i)$ denote the firm that serves her, the ZIP code she lives in, and the month of her start of home health care, respectively. Define $P_{\hat{i}}$ as the set of patients other than patient i who have the vector of these three characteristics $(f(i),\ z(i),\ m(i))$, where the hat denotes omission.

[12] The description of my empirical analysis using the 2SLS estimation follows that done by Doyle Jr et al. (2015).

That is:

$$P_{\hat{i}} := \{j | j \neq i,\ (f(j),\ z(j),\ m(j)) = (f(i),\ z(i),\ m(i))\}.$$

Finally let $v_{j,w}$ be the number of nurse visits provided to each patient $j \in P_{\hat{i}}$ by nurses in work arrangement w. w can be one of the six arrangements: 1) full-time, 2) part-time with benefits, 3) part-time without benefits, 4) on-call, 5) contractor, and 6) office/other. For each i, the activeness of full-time nurses is then defined as

$$Active_i = \frac{\sum_{j \in P_{\hat{i}}} v_{j,full-time}}{\sum_w \sum_{j \in P_{\hat{i}}} v_{j,w}}. \tag{1.1}$$

I exclude the given patient episode i from this measure to avoid predicting the patient's fraction of full-time nurse visits using her own full-time nurses' visits. This leave-out method has been used in previous literature (Angrist Joshua and Pischke, 2009; Doyle Jr et al., 2015).

The quasi-experimental set up here is comparing two patients served by the same firm in two different ways. The first comparison is cross-sectional—comparing two patients who started home health care at the same month but lived in different ZIP codes. Here one patient may have happened to live in a ZIP code area where full-time nurses were more active than other nurses. The second comparison is cross-time—comparing two patients who lived in the same ZIP code but started in different months. Here one patient may have happened to start care when full-time nurses were more active.

I illustrate how these two variations in the activeness instrument explain the proportion of full-time nurse visits in Table 3. Panel A shows that in ZIP codes where full-time nurses were more active (i.e. above or equal to median), patients had 16 percentage points higher proportion of full-time nurse visits even within the same firm-month pairs. The median values are created for each firm-month pair using the patient's start-of-care month. The difference is statistically significant at the one percent level by the t-test of the equality of the means. Panel B shows that when patients happened to start care in months during which full-time nurses were more active, they received 20 percentage points higher proportion of full-time nurse visits within the same firm-ZIP code pairs. This difference is also statistically significant at the one percent level.

1.5.2. Empirical Specifications

First, I model the first-stage relationships between the patient i's proportion of full-time nurse visits FTV_i and the instrument variable Z_i, $Active_i$, at the patient episode level. For each patient episode i who is served by firm $f(i)$, lives in ZIP code $z(i)$, and has her home health care start in month $m(i)$ and end in time period $t(i)$, her proportion of full-time nurse visits FTV_i is a function of the form:

$$FTV_i = \alpha_0 + \alpha_1 Z_i + \gamma X_i + \delta_{f(i)} + \zeta_{z(i)} + \eta_{m(i)} + \theta_{t(i)} + \nu_{i,f(i),z(i),m(i),t(i)}. \tag{1.2}$$

The vector X_i includes observed patient characteristics including the number of nurse hand-offs, total number of nurse visits, mean interval of nurse visits (i.e. mean number of days between two consecutive nurse visits), a set of firm level service demand and labor demand characteristics, a set of hospitalization risk controls, a set of demographic controls, and a set of comorbidity controls. The set of firm level service demand and labor demand controls includes mean of firm-day level variables capturing the caseload and labor supply conditions in each firm across the patient's home health days. The firm-day level variables include the number of ongoing episodes, the number of active nurses, and the fraction of active piece-rate nurses working in an firm-day cell. The set of hospitalization risk controls represents a set of indicator variables associated with high risk of hospitalization, and includes history of 2 or more falls in the past 12 months, 2 or more hospitalizations in the past 6 months, a decline in mental, emotional, or behavioral status in the past 3 months, currently taking 5 or more medications, and others. The set of demographic controls includes six 5-year age group dummies for ages ranging from 65-94 (age 95 or higher is an omitted group), gender, race, insurance type, an indicator for having no informal care assistance available, and an indicator for living alone.[13] The set of comorbidity controls includes a Charlson comorbidity index, indicators for overall health status, indicators for high-risk factors including alcohol dependency, drug dependency, smoking, obesity, and indicators for conditions prior to hospital stay within past 14 days including disruptive or socially inappropriate behavior, impaired decision making, indwelling or suprapublic catheter, intractable pain, serious memory loss and/or urinary incontinence.[14] $\nu_{i,f(i),z(i),m(i),t(i)}$ is an idiosyncratic error.

Controlling for the number of handoffs and total number of nurse visits in the regression equation is important. Experiencing a mix of permanent and temporary labor during patient care inevitably involves switching of providers or "handoffs," which may independently affect the patient outcome. Fewer handoffs mechanically lead to either one or zero proportion of full-time nurse visits: this is illustrated in Table 2 with much smaller ratio of handoffs to nurse visits for Groups 1 and 4, who received zero and 100 percent of full-time nurse visits, respectively. In Chapter 3 of this dissertation, I find nurse handoffs—defined as being visited by a different nurse than the last one—to substantially increase the probability of readmission.[15] In addition, sicker patients may receive more nurse visits, which affects the proportion of full-time nurse visits and the likelihood of readmission.

I also include a set of fixed effects for firm, patient ZIP code, start-of-care month, and end-of-care time period, where the time period refers to the day of week (6 dummies), week of year (52 dummies), and year (4 dummies). Therefore, this estimation compares patients in two ways, as explained above. First, it compares patients who were served by the same firm, started care in the same month and ended home health care at the same time but lived in different ZIP codes having a different level of activeness or preoccupied nearest full-time

[13] Insurance types include Medicare Advantage (MA) plans with a visit-based reimbursement, MA plans with an episode-based reimbursement, and dual eligible with Medicaid enrollment (reference group is Medicare FFS).

[14] Indicators for overall health status include indicators for very bad (patient has serious progressive conditions that could lead to death within a year), bad (patient is likely to remain in fragile health) and temporarily bad (temporary facing high health risks).

[15] Although handoffs are found to be an important determinant of readmission in Chapter 3, I do not treat it as an endogenous variable to be instrumented for in this specification. The reason is that my instrument for the proportion of full-time nurses poorly capture the variation of handoffs. Since the causal effect of handoffs is not of main interest in this chapter, I just control for it as an explanatory variable.

nurses. Second, the regression compares patients who were served by the same firm, lived in the same ZIP code, and ended home health care at the same time but had a different level of activeness or preoccupied nearest full-time nurses at the start of care.

The main estimating model for the second-stage relationship between the proportion of full-time nurse visits and patient readmission takes the form

$$Readmit_i = \beta_0 + \beta_1 FTV_i + \gamma X_i + \delta_{f(i)} + \zeta_{z(i)} + \eta_{m(i)} + \theta_{t(i)} + \epsilon_{i,f(i),z(i),m(i),t(i)}. \tag{1.3}$$

where $Readmit_i$ is an indicator variable for hospital readmission of a patient episode i. I compare the OLS estimation of equation 1.3 with its 2SLS estimation using the instruments explained above. This comparison will show the importance of taking into account the non-random assignment of full-time nurse visits in identifying the effect of labor mix on patient readmission. I estimate a linear probability model.

1.5.3. Potential Limitations

There are potential concerns about the instruments. First, there could be unobserved ZIP code-month level shocks that are correlated with the full-time nurses' activeness and the patient readmission. For example, do demographic changes such as a surge in the elderly population in a given ZIP code-month pair affect both full-time nurses' activeness and patient readmission? A lack of availability of such high-frequency ZIP code level information makes it hard to directly control for these relevant ZIP code-month level controls. However, for example, if an elderly population grows in a ZIP code in a given month, the omitted variable bias is expected to work against finding a negative effect of full-time nurse visits on readmission. The reason is that full-time nurses would become more active due to increased home health care demand while the readmission would be more likely among the elderly.

Second, firms may selectively admit patients into home health care based on the full-time nurses' activeness. To the extent that firms admit healthier patients into home health care when full-time nurses were more active, I will likely overstate the negative effect of full-time nurse visits on patient readmission. To allay this concern, I investigate the balancing of observed characteristics by whether the patient had high or low activeness of full-time nurses. High values are marked by whether the activeness is above or equal to median. Table 4 reports the mean values of regression controls for the two groups of patients. The first row in Panel A shows that when full-time nurses are more active, patients' proportion of full-time nurse visits is higher, as expected. When patients had high activeness of full-time nurses, they had nearly double the proportion of full-time nurse visits in column (2) by 40 percentage points, compared to patients who had low activeness in column (1). The hospital readmission rate is also greater for patients with high activeness of full-time nurses. Simultaneously, the hospitalization risk factors in Panel C and comorbidity characteristics in Panel E show that patients with high activeness of full-time nurses were indeed sicker. On average, these patients had higher Charlson comorbidity index and higher likelihood of having their overall status to remain in fragile health. Thus, I can refute the concern that firms may selective admit healthier patients when full-time nurses are more active. It was rather the opposite: firms tended to admit sicker patients when full-time nurses were more active, which works against finding a negative effect of full-time nurse visits on readmission.

1.6. Results

1.6.1. First-Stage Results on the Proportion of Full-Time Nurse Visits

Table 5 shows the first-stage results on the relationship between the proportion of full-time nurse visits and my instrument—full nurses' activeness in the patient's ZIP code—in equation (1.2). Standard errors in these models are clustered at both the firm and patient ZIP code levels.

In column (1), I begin by estimating the equation with fixed effects for each firm and ZIP code, respectively, and end-of-care time fixed effects for the week of year, year, and day of week. I also control for the number of nurse handoffs, total number of nurse visits, mean interval of nurse visits and office-week level overall demand and labor supply characteristics.

I incrementally control for more patient characteristics in columns (2)–(4).

There is a strong correlation between the patient's proportion of full-time nurse visits and my instrument, as shown by the statistically significant correlations at the one percent level and large F-statistic values of around 300. In column (4) for the richest specification, when full-time nurses were more active in the patient's ZIP code during the start-of-care month by one standard deviation (0.26), she received 16 percentage points or 26 percent higher proportion of full-time nurse visits given the mean of 0.6.[16] This would translate to nearly one more full-time nurse visit during her care which involved six total nurse visits on average.

1.6.2. Second-Stage Results on Patient Readmission

I begin with the OLS estimation of the effect of the proportion of full-time nurse visits on patient readmission in equation (1.3). Panel A shows that the proportion of full-time nurse visits is negatively correlated with an indicator for hospital readmission: patients receiving a one-standard-deviation higher proportion of full-time nurse visits (0.41) were 0.4 percentage points or 2 percent less likely to be readmitted given the mean readmission rate of 0.2. However, this effect is not statistically significant even at the 10 percent level in all columns. This result reflects the upward bias I described in Section 1.4, which likely occurs since sicker patients tended to have a higher proportion of full-time nurse visits. Indeed, the coefficient decreases twofold from column (1) to (2), and threefold from column (1) to (4). This pattern corroborates that sicker patients in terms of hospitalization risk controls, demographic controls and comorbidity controls were systematically assigned a higher proportion of full-time nurse visits while those patients were independently more likely to be readmitted.

Panel B shows the 2SLS estimates using the first-stage results from Table 5. There is a stronger negative correlation between the proportion of full-time nurse visits and hospital

[16] A 26-percent increase is obtained by multiplying the one standard deviation, 0.26, by the coefficient estimate 0.608 and dividing by the mean proportion of full-time nurse visits 0.6 (with the final number multipled by 100 for the percentage).

readmission by almost four times. The effects are statistically significant at the ten percent level once hospitalization risk, demographic, and comorbidity controls are included in columns (2)–(4). The rise of statistical significance reflects, shown in Section 1.5.3, that sicker patients were more likely to be admitted when full-time nurses were active—which works against estimating a negative effect of full-time nurse visits on readmission. This pattern also contributes to reducing the precision of the estimates. On the other hand, the estimated effects of full-time nurse visits on readmission can be viewed as conservative. From the richest specification in column (4), I find that patients having a one-standard-deviation (0.41) higher proportion of full-time nurse visits or about 2 more full-time nurse visits were 1.4 percentage points or 7 percent less likely to be readmitted.

1.7. Conclusion

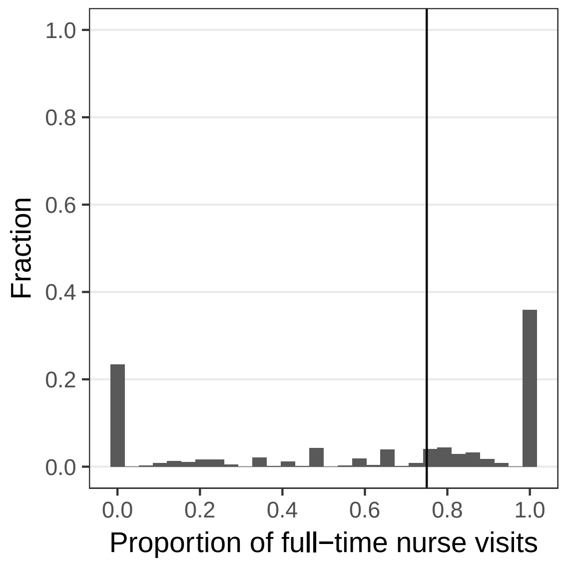
Alternative work arrangements are becoming increasingly popular modes of labor contracts in many industries due to the appeal of the flexibility and potential labor cost reductions. Health care, a labor-intensive service industry facing demand uncertainty, particularly has experienced one of the largest increases in the use of alternative work arrangements over the past two decades. These arrangements might be particularly necessary for supplementing labor supply in the presence of state regulations of the minimum nurse staffing levels and staffing shortages (Tong, 2011; Cook et al., 2012; Mark et al., 2013; Lin, 2014; Matsudaira, 2014). Therefore, it is crucial to understand whether providers hired in traditional and alternative work arrangements lead to any difference in the quality of care and performance.

However, estimating this hypothesis is challenging due to confounding factors and non-random matching of patients and providers in particular work arrangements, as described above. Home health care and the dataset I use provide an ideal opportunity to overcome these challenges and investigate the effect of full-time nurse visits on patient readmission. Home health is also an important market to study as it is one of the fastest growing sectors of health care, and is a sector in which a large proportion of the workforce is hired in alternative work arrangements.

I find that patients receiving a higher proportion of full-time nurse visits were less likely to be readmitted. This finding is obtained by exploiting an exogenous variation across ZIP codes and care timings in the proportion of full-time nurse visits from full-time nurses' activeness. Moreover, this effect holds after controlling for patients' underlying health characteristics, office-level demand and labor supply characteristics, patients' ZIP code fixed effects, firm fixed effects, month fixed effects and fixed effects related to the timings of the start and end of care.

My findings suggest that increasing the use of full-time nurses can improve the quality of care. It will be a fruitful target for policymakers and providers to focus on understanding the determinants of and reducing the gap in quality provided by nurses in different work arrangements. Consequently, future work on the specific mechanisms underlying my finding is critical. If experience were an important determinant of quality difference between full-time nurses and others, it is crucial to investigate nurses' learning curve, which also has broader implication on the choice of work arrangements and the value of retention. Furthermore, future work on the variation in the gap in quality of care among nurses in different work arrangements across different firms is crucial. Organizational learning by doing on the management and configuration of alternative work arrangements will provide valuable insights.

Figure 1: Variation in the Proportion of Full-Time Nurse Visits across Patient Episodes



Notes: The unit of observation is a patient episode. The vertical line denotes the median value, 0.75.

Table 1: Labor Supply and Pay Characteristics of Nurses by Work Arrangements

	(1) Full-time	(2) Part-time with benefits	(3) Part-time without benefits	(4) On-call	(5) Contractor	(6) Office/ Other
A. Labor supply characteristics per week						
Number of visits	21.84	15.93	14.53	8.93	6.46	10.76
Number of days worked	4.95	4.51	4.35	3.45	2.27	3.40
Total time spent on visits (hours)	16.16	12.15	11.49	6.94	5.57	8.24
Mean visit length (hours)	0.77	0.79	0.80	0.84	0.87	0.85
Length of employment (months)	21.18	24.41	28.29	16.29	5.18	8.33
B. Pay characteristics						
Pay scheme	Salary	Salary	Salary	Piece rate	Piece rate	Salary
Total weekly pay ($)	1,239.27	819.25	711.91	445.06		
Per visit rate ($)	43.77	42.30	42.70	55.80		

Notes. The first four variables in Panel A are obtained using weeks during which the nurses provided at least one visit. The length of employment in Panel A is measured for nurses who terminated their employment, where the termination is defined as either permanently exiting the workforce or providing no visits for more than 90 consecutive days. For the pay scheme in Panel B, salary is defined as a fixed amount of pay for the specific expected number of visits per week, and piece rate as a fixed rate per visit. Salaried nurses are eligible for benefits, except part-time nurses without benefits in column (3); piece-rate paid ones are ineligible.

Table 2: Patient Severity and the Proportion of Full-Time Nurse Visits

Proportion of full-time nurse visits	(1) 0	(2) Greater than 0 and less than median	(3) At least median and less than 1	(4) 1
A. Key endogenous determinants of the patient readmission				
Proportion of full-time nurse visits	0.00	0.43	0.82	1.00
Ratio of handoffs to nurse visits	0.11	0.43	0.33	0.15
Number of nurse visits	5.61	5.92	7.20	5.42
Mean number of days between two consecutive visits	4.86	4.78	4.88	5.32
B. Hospitalization risk factors				
Risk for hospitalization: History of 2+ falls	0.26	0.25	0.26	0.26
Risk for hospitalization: 2+ hospitalizations	0.35	0.40	0.43	0.40
Risk for hospitalization: Recent mental decline	0.06	0.07	0.07	0.08
Risk for hospitalization: Take 5+ medications	0.87	0.88	0.88	0.89
Risk for hospitalization: Other	0.07	0.11	0.08	0.10
C. Demographic characteristics				
Age	79.24	78.39	78.82	78.92
Female	0.58	0.59	0.61	0.62
White	0.83	0.80	0.79	0.77
Enrolled in per-visit paying Medicare Advantage	0.22	0.17	0.16	0.17
Enrolled in per-episode paying Medicare Advantage	0.08	0.04	0.04	0.04
Dual eligible	0.00	0.01	0.01	0.01
No assistance available	0.02	0.02	0.02	0.02
Living alone	0.23	0.23	0.26	0.25
D. Comorbidity characteristics				
Overall status having serious progressive conditions (Very bad)	0.02	0.03	0.04	0.04
Overall status likely to remain in fragile health (Bad)	0.27	0.29	0.30	0.32
Overall status temporarily facing high health risks (Less bad)	0.63	0.59	0.60	0.58
High risk factor: Alcohol dependency	0.03	0.02	0.02	0.03
High risk factor: Drug dependency	0.01	0.01	0.01	0.01
High risk factor: Heavy smoking	0.13	0.13	0.13	0.14
High risk factor: Obesity	0.17	0.19	0.18	0.16
Pre-home health condition: Disruptive behavior	0.01	0.01	0.01	0.01
Pre-home health condition: Impaired decision-making	0.12	0.15	0.14	0.17
Pre-home health condition: Indwelling/Suprapubic catheter	0.02	0.02	0.02	0.01
Pre-home health condition: Intractable pain	0.12	0.12	0.09	0.11
Pre-home health condition: Memory loss	0.10	0.10	0.10	0.12
Pre-home health condition: Urinary incontinence	0.27	0.29	0.30	0.31
E. Other characteristics				
Length of care (in days)	24.42	25.14	31.05	25.36
Total number of unique nurses seen	1.46	2.82	2.65	1.58
Number of physical therapy visits	4.26	4.14	4.66	4.36
Number of occupational therapy visits	1.22	1.35	1.59	1.46
Number of speech therapy visits	0.22	0.27	0.32	0.30
Number of home health aide visits	0.60	0.66	0.83	0.59
Number of observations	4,975	4,927	3,672	7,626

Notes. The median proportion of full-time nurse visits is 0.75.

Table 3: Mean Proportion of Full-Time Nurse Visits by Full-Time Nurses' Activeness in the Local Area at the Start of Care

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Within firm-month pairs			B. Within firm-ZIP code pairs		
Instrument	Above or equal to median	Below median	Difference (1) - (2)	Above or equal to median	Below median	Difference (4) - (5)
Full-time nurses' activeness	0.69	0.53	0.16***	0.72	0.51	0.20***

Notes. Each cell reports the mean proportion of full-time nurses. The columns (3) and (6) show the statistical significance from the t-test of the null hypothesis that the two mean values between above/equal to median and below median ZIP codes (in Panel A) or months (in Panel B) are equal to each other. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4: Balance of Covariates in the Patient Sample

Full-time nurses' activeness	(1) Low	(2) High
A. Key variables of interest		
Proportion of full-time nurse visits	0.42	0.78
Indicator for hospital readmission	0.19	0.21
B. Care characteristics		
Number of nurse handoffs	1.26	1.53
Number of nurse visits	5.96	5.82
Mean number of days between two consecutive visits	4.85	5.18
C. Hospitalization risk factors		
Risk for hospitalization: History of 2+ falls	0.26	0.26
Risk for hospitalization: 2+ hospitalizations	0.37	0.41
Risk for hospitalization: Recent mental decline	0.07	0.07
Risk for hospitalization: Take 5+ medications	0.87	0.89
Risk for hospitalization: Other	0.09	0.10
D. Demographic characteristics		
Age	79.14	78.58
Female	0.60	0.61
White	0.83	0.76
Enrolled in per-visit paying Medicare Advantage	0.20	0.16
Enrolled in per-episode paying Medicare Advantage	0.06	0.04
Dual eligible	0.00	0.01
No assistance available	0.02	0.02
Living alone	0.24	0.24
E. Comorbidity characteristics		
Charlson Comorbidity Index	0.63	0.70
Overall status having serious progressive conditions (Very bad)	0.03	0.04
Overall status likely to remain in fragile health (Bad)	0.28	0.31
Overall status temporarily facing high health risks (Less bad)	0.61	0.58
High risk factor: Alcohol dependency	0.03	0.02
High risk factor: Drug dependency	0.01	0.01
High risk factor: Heavy smoking	0.13	0.14
High risk factor: Obesity	0.17	0.18
Pre-home health condition: Disruptive behavior	0.01	0.01
Pre-home health condition: Impaired decision-making	0.14	0.16
Pre-home health condition: Indwelling/Suprapublic catheter	0.02	0.02
Pre-home health condition: Intractable pain	0.11	0.12
Pre-home health condition: Memory loss	0.11	0.10
Pre-home health condition: Urinary incontinence	0.29	0.30
F. Firm characteristics		
Mean daily number of episodes in the office	170.54	192.59
Mean daily number of active nurses in the office	21.60	22.00
Mean daily proportion of full-time nurses in the office	0.41	0.54
Number of observations	10,600	10,600

Notes. Mean values are reported. The "High" group of patients is defined as those whose full-time nurses' activeness is above or equal to median. The median thresholds used for grouping patients is 0.66 for the full-time nurses' activeness.

Table 5: IV First-Stage Results: Effect of Full-time Nurses' Activeness on the Proportion of Full-Time Nurse Visits

	Dep. var.: Proportion of full-time nurse visits			
	(1)	(2)	(3)	(4)
Full-time nurses' activity share	0.602***	0.602***	0.602***	0.600***
	(0.034)	(0.035)	(0.035)	(0.035)
R-squared	0.32	0.32	0.33	0.33
F-statistic	307.20	301.83	299.66	301.47
Hospitalization risk controls	.	Yes	Yes	Yes
Demographic controls	.	.	Yes	Yes
Comorbidity controls	.	.	.	Yes
Observations	21,200	21,200	21,200	21,200

Source. Authors' proprietary data. *Notes.* The unit of observation is a patient episode. In all columns, I control for the number of nurse handoffs, total number of nurse visits, mean interval of nurse visits, mean of firm-day level demand and labor supply characteristics during the patient's episode; and firm fixed effects, patient's ZIP code fixed effects, fixed effects for day of week, week of year, and year of the last day of care, respectively. Firm-ZIP code level clustered standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: Main Results: Effect of Proportion of Full-Time Nurse Visits on Patient Readmission

	Dep var: Indicator for hospital readmission			
	(1)	(2)	(3)	(4)
	A. OLS			
Proportion of full-time nurse visits	-0.003	-0.007	-0.007	-0.009
	(0.013)	(0.010)	(0.010)	(0.009)
R-squared	0.13	0.15	0.15	0.18
	B. 2SLS			
Proportion of full-time nurse visits	-0.032	-0.036*	-0.035*	-0.035*
	(0.021)	(0.020)	(0.020)	(0.020)
R-squared	0.02	0.02	0.02	0.02
Hospitalization risk controls	.	Yes	Yes	Yes
Demographic controls	.	.	Yes	Yes
Comorbidity controls	.	.	.	Yes
Observations	21,200	21,200	21,200	21,200

Source. Authors' proprietary data. *Notes.* The unit of observation is a patient episode. I use a a two-step efficient generalized method of moments (GMM) estimator. In all columns, I control for the number of nurse handoffs, total number of nurse visits, mean interval of nurse visits, mean of firm-day level demand and labor supply characteristics during the patient's episode; and firm fixed effects, patient's ZIP code fixed effects, fixed effects for day of week, week of year, and year of the last day of care, respectively. Firm-ZIP code level clustered standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

CHAPTER 2 : The Effect of Reputation on Firms' Labor Mix Strategy under Demand Uncertainty

2.1. Introduction

One of the fundamental challenges for labor-intensive service firms facing demand uncertainty is how to configure their workforce to improve service quality and performance. In particular, such firms must decide on a mix of temporary and permanent workers to deal with fluctuations in demand. Existing economic literature has shown that firms rely more on temporary workers when facing greater demand fluctuations due to either the opportunity cost of keeping an idle workforce (Dixit and Pindyck, 1994; Foote and Folta, 2002; Lotti and Viviano, 2012) or the cost associated with high turnover rate (Rebitzer and Taylor, 1991; Levin, 2002). However, this does not take into account that permanent and temporary workers may not be perfectly interchangeable in production. In particular, there is evidence that permanent workers outperform temporary workers in terms of the quality of service provided, as shown in Chapter 1 of this dissertation (Bae et al., 2010; Pham et al., 2011; Lotti and Viviano, 2012; Lu and Lu, 2016). Thus, how firms configure their workforce depends crucially on the following trade-off: temporary workers provide greater flexibility in responding to fluctuation in demand but may impede the establishment of firm reputation through lower quality of service. Despite the salience of this trade-off—particularly to younger firms, which face both greater demand fluctuations and a greater need to demonstrate high quality to their clientele—its incorporation is largely absent from the existing literature. This may be due to a paucity of high-frequency longitudinal data containing firms' labor configurations and patient demand allocation. In this chapter, using novel data from the home health industry, I aim to fill this gap and paint a more complete picture of service firms' temporary labor strategy.

I present and test a simple model of firms' labor mix choices, highlighting the role of reputation in determining how firms optimally balance the trade-off between responding to demand shocks and improving quality. Vast literature has shown the crucial role of reputation in determining quality (Klein and Leffler, 1981; Carmichael, 1984; McMillan and Woodruff, 1999; Banerjee and Duflo, 2000; Baker et al., 2002; Macchiavello and Morjaria, 2015) and demand (Navathe and David, 2009; Johnson, 2011) in the presence of non-enforceable contracts. In service industries, demand is often non-contractible either due to the nature of service provision, organizational structure or a regulatory ban. Thus, the perception of a firm's service quality, which forms a basis of the firm's reputation, becomes an important determinant of demand faced by the firm. Particularly in health care, provider firms compete on quality since prices are often administered and consumers show little price sensitivity due to generous health insurance. The competitive reallocation forces have been shown to encourage providers to improve quality (Johnson, 2011; Chandra et al., 2016). Therefore, reputation concerns are likely to prevail in health care and shape firms' labor mix decisions in the presence of trade-offs in using temporary workers.

To build intuition for the role of reputation in determining firms' labor mix choices, consider the start-ups Munchery and Instacart, which provide on-demand grocery delivery service. These start-ups initially used independently contracted drivers to perform all the tasks. However, due to high turnover and quality deterioration, the firms completely eliminated or diminished the role of temporary workers particularly in tasks that are likely to determine the quality of service.[1] These cases suggest that the importance of reputation building among starting firms makes them prioritize providing higher quality over purely optimizing cost and rely more on permanent workers.

Making this intuition more rigorous, my model posits that a firm's labor mix influences the market's perception of the firm's quality, and the firm's demand is in turn stochastically linked to its reputation for quality. Underlying this mechanism is a process of dynamic reputation formation in which the market observes the firm's quality signals and updates the firm's reputation. This model is built on Navathe and David (2009)'s model of physi-

[1] "A middle ground between contract worker and employee" by Noam Scheiber, *New York Times*, December 10, 2015.

cians' technology adoption behavior under reputation concerns but I extend the model to a stochastic optimal control problem to incorporate demand uncertainty.

I explicitly model the trade-off involved in the labor mix choice. On the one hand, the proportion of demand served by permanent workers increases quality signals, and thus increases reputation. This key assumption is supported by my finding in Chapter 1 of this dissertation. I find that patients receiving a higher proportion of full-time nurse visits during care were less likely to be readmitted to a hospital. This evidence validates my model assumption and validates my claim that firms are faced with a trade-off in using temporary workers between flexibility and quality.

On the other hand, permanent workers reduce the firm's expected short-term profitability since the firm hires them before observing the demand realization. Therefore, the firm optimally balances across time the long-term reputation gain from increasing the share of permanent workers with the reduction in short-term profitability. The central predictions of the model are that firms with lower reputation increase the share of permanent workers in response to demand volatility to achieve long-term gain in reputation. In contrast, firms with higher reputation decrease the share of permanent workers to reduce short-term profit loss.

I test the predictions of the model using data from a large US home health provider operating 106 autonomous offices in 18 states during 2012-2015. Each office with its own director having full authority on the labor configuration and management is treated as a separate firm. The data contain the entire home health visit records in each firm showing all the interactions between a patient and individual providers who served her, as well as human resources characteristics such as providers' employment arrangements and weekly pays. Moreover, for each patient, the data contain referral sources, which allow me to track the establishment of strong referral networks in each firm and use this as a proxy for the firm's reputation. I can measure reputation in various ways: the size of referral network, referral dispersion, referral consistency, and referral share from each source. Combining these data, I construct weekly longitudinal data for each firm containing labor configuration, demand environments, as well as measures of reputation.

In the cross-sectional analysis with firm fixed effects, I examine the relationship between firms' percentage of full-time nurses and demand volatility, and whether this relationship varies with various measures of reputation. I find evidence consistent with both predictions of my model. I find that firms with a lower reputation stock increased the percentage of full-time nurses with demand volatility. Firms in the bottom third of the within-firm age-specific distribution in terms of referral network size and referral consistency hired 0.2-0.3 more full-time nurse in the mean nursing workforce size of 21 nurses when demand volatility increased by one standard deviation. In particular, young firms aged 0–12 months hired 0.5 to 1 more full-time nurses and hired 0.5 fewer contractor nurses given the mean total workforce size of 13 nurses when demand volatility increased by one standard deviation. Considering firms' age as a proxy of reputation, this stronger correlation among the young firms provides further support to my model. Moreover, this result was not confounded by the size effect: it was only the large young firms that hired more full-time nurses when they had a small referral network and low referral consistency. In contrast, I find the positive association between the percentage of full-time nurses and demand volatility disappears when firms' reputation increased. These results suggest that low-reputation firms forgo short-term profitability to achieve long-term reputation through quality improvement.

This chapter contributes novel empirical evidence that firms' labor mix strategies crucially depend on their reputation and provides a theoretical model to explain this. Although traditional theory suggests that firms should decrease the share of permanent labor in the face of increased demand volatility, my data indicate the opposite and counterintuitive story. Less established firms such as starting firms rather increase the share of permanent workers in response to demand volatility. This phenomenon cannot be explained if only demand shocks are considered as a determinant of labor mix. I propose that this may be explained by taking into consideration a firm's concern for building reputation.

This chapter is related to and builds upon several topics in the literature. Most closely related is work studying the relationship between demand uncertainty and labor input choices (Rebitzer and Taylor, 1991; Abraham and Taylor, 1996; Levin, 2002; Lotti and Viviano, 2012) and more broadly work on input choice under uncertainty (Oi, 1961; Nadiri and Rosen, 1973; Sandmo, 1971; Batra and Ullah, 1974; Hartman, 1976; Friedman and Pauly, 1981; Guiso and Parigi, 1999; Baker et al., 2004). The chapter is also related to literature on the role of reputation in determining firms' quality or commitment to non-enforceable contracts (Klein and Leffler, 1981; McMillan and Woodruff, 1999; Banerjee and Duflo, 2000; Navathe and David, 2009; Johnson, 2011; Macchiavello and Morjaria, 2015).

The remainder of this chapter is organized as follows. In Section 2.2, I provide background on home health care and the employment arrangements used by home health firms in the data. In Section 2.3, I present a model of firms' labor mix choices. In Section 2.4, I describe the data and sample restriction rules. In Section 2.5, I describe the evolution of firm's demand volatility, labor mix, and reputation by firm age. In Section 2.6, I conduct empirical analysis of the effect of reputation on firms' labor mix and report results. In Section 2.7, I discuss possible alternative explanations for my empirical results and conduct robustness checks. In Section 2.8, I conclude the chapter.

2.2. Background on Home Health Care

Home health care, which is provided to homebound patients who need skilled nursing or therapy services, is an important and rapidly growing segment of the post-acute care delivery system. I provide more details on the home health care industry and home health care professionals in Appendices A.1 and A.2, respectively, at the end of the dissertation.

Home health is an ideal setting to investigate the impact of reputation on firms' labor mix choices. It is labor intensive, less technology-dependent, and decentralized (David and Polsky, 2014), as patients receive services in their homes, making it easier to attribute patient outcomes to workforce configuration. Moreover, quality is a critical dimension on which firms compete since public insurance, i.e. Medicare, is a primary payer with prospective payment and thus prices are administered (Gaynor et al., 2014). Furthermore, referrals from other health care facilities are a primary source of new demand for home health care firms. However, the federal Anti-Kickback Statute bans formally contracting with referral sources for the number of referrals, thus elevating the importance of reputation as a driver of firms' demand volume. The statute also has the effect of making demand inherently uncertain and consequently increasing the importance of temporary labor as a source of labor supply.

In this chapter, I focus on the skilled nursing workforce—combination of registered nurses (RNs) and licensed practice nurses (LPNs)—since nurses provide the most medically relevant service that could potentially determine hospital readmissions and accounts for a majority of the home health visits. Thus, home health firms have the largest demand for skilled nurses and maintain the largest capacity of them each week.

2.3. Theory

Consider a risk-neutral home health firm and many risk-neutral referral sources (e.g., hospitals) which can refer patients to the firm and determine the quantity of home health demand Q_t faced by the firm in periods $t = 0, 1, \ldots$. A firm hires workers mainly in two work arrangements: salary (for permanent positions) and piece-rate pay (for temporary positions). The difference lies in the fact that salaried workers are hired before observing demand while piece-rate paid workers can be hired after observing demand.

The sequence of events is as follows. At the beginning of a period t, the firm's reputation for quality among referral sources is R_t.[2] The demand the firm faces is influenced by its reputation, but remains stochastic overall. The firm must choose how many salaried workers to hire in advance of observing the actual demand in period t. The market then views the fraction of demand served by salaried workers as a quality signal and updates its judgment

[2] I assume the reputation in the initial period 0 to be some fixed value below the market average.

of the firm's reputation for the next period accordingly.

In a little more detail, let s_t and p_t denote labor demand for salaried and piece-rate paid workers, respectively. Assume that the units of labor demand are equal to the units of home health demand for simplicity. The firm hires salaried workers s_t before observing demand Q_t. The firm hires piece-rate labor p_t if demand exceeds salaried labor, i.e. $Q_t > s_t$. Therefore,

$$Q_t \geqslant \min(s_t, Q_t) + p_t. \tag{2.1}$$

The firm's proportion of salaried labor s_t/Q_t impacts the firm's reputation in the next period $t+1$.

Denote the price per unit of demand by α. The price is constant since the primary payer of home health services is Medicare FFS, which has a prospective payment system. Assume that this marginal revenue α exceeds the marginal cost of serving demand, i.e. marginal cost of labor for either type of workers. Then it is always profitable to serve all the demand that arrives at the firm. Thus, the firm does not turn away any patients, and the constraint (2.1) always holds with equality.[3] Rearranging terms, this means the temporary labor demand p_t is given by

$$\begin{align} p_t &= Q_t - \min(s_t, Q_t) \tag{2.2} \\ &= \begin{cases} 0 & \text{if } s_t \geqslant Q_t \\ Q_t - s_t & \text{otherwise} \end{cases} \tag{2.3} \end{align}$$

To model how the firm's reputation for quality is formed over time, suppose that its reputation stock dynamically evolves as a combination of the history of reputation stocks and new quality signals. Thus, I can write the next period's reputation stock R_{t+1} as a function

[3] I conjecture that relaxing this assumption of no turning away of patients would reinforce the model's predictions because low-reputation firms would also want to reduce turnaway probability in addition to increasing the share of salaried labor.

of the current period's reputation stock R_t and the current period's quality signal φ_t.

$$R_{t+1} = f(R_t, \varphi_t) \tag{2.4}$$

where f' is positive with respect to each argument.

In this chapter, I focus on hospital readmission rate as the main quality signal. Hospitals view readmissions as a critical measure of the home health firm's quality since the Hospital Readmissions Reduction Program (HRRP) instituted under the Affordable Care Act (ACA) imposes financial penalties on hospitals with high readmission rates starting from fiscal year 2012. The HRRP has shown to be effective in reducing readmissions (Gupta, 2016). As post-acute care entities can play a significant role in preventing avoidable readmissions, hospitals prefer to refer to freestanding home health agencies that achieve lower hospital readmissions (Worth, 2014). This referral preference would be reinforced by competitive demand reallocation forces, which have been shown to work in hospital markets (Chandra et al., 2016).

Labor mix is a crucial determinant of quality signals in health care, as shown by previous literature which examines the impact of temporary nurses on patient outcomes (Bae et al., 2010; Hockenberry and Becker, 2016; Lu and Lu, 2016). I also show in Chapter 1 of this dissertation that in the home health, labor mix measured by the proportion of full-time nurse visits increases hospital readmission. Therefore, built on this evidence, I make a key assumption that a higher proportion of salaried workers improve high-quality signals. Higher quality workers are more likely to command a permanent position, typically have more experience, longer engagement with the firm and superior knowledge of its culture and standards. On the other hand, permanent workers may have lower incentive to exert high effort if they expect longer tenure in the firm (Rebitzer and Taylor, 1991) or have shorter interaction with each patient due to higher workloads.

I model the link between the firm's demand quantity and reputation. Suppose that the quantity of demand Q_t is stochastically determined by reputation stock R_t:

$$Q_t = g(R_t) \tag{2.5}$$

where $g'(\cdot) > 0$, implying that firms with greater reputation for quality receive higher demand. This is a reasonable assumption since, with administered prices, firms compete on non-price dimensions. It is standard to assume that the firm's market share increases with quality (Gaynor et al., 2014).

The firm's objective is to maximize expected present discounted value of the profit subject to the constraint (2.2):

$$V_t(R_t) = \max_{\{s_t\}_{t=0}^{\infty}, \{p_t\}_{t=0}^{\infty}} \mathbb{E} \sum_t \beta^t (\alpha Q_t(R_t) - c_s(s_t) - c_p(p_t)) \tag{2.6}$$

$$\text{subject to} \quad p_t = Q_t(R_t) - \min(s_t, Q_t(R_t)). \tag{2.7}$$

After plugging in the constraint (2.2) and rearranging terms, I obtain the following Bellman equation:

$$V_t(R_t) = \max_{s_t} \mathbb{E}\pi(s_t, R_t) + \beta \mathbb{E} V(R_{t+1}) \tag{2.8}$$

where

$$\pi(s_t, R_t) \equiv \alpha Q_t(R_t) - c_s(s_t) - c_p(Q_t(R_t) - \min(s_t, Q_t(R_t))).$$

In a general form, the expected profit for period t is given by

$$\mathbb{E}\pi(s_t, R_t) = \alpha Q_t(R_t) - c_s(s_t) + \int_{Q_t(R_t) > s_t} c_p(Q_t(R_t) - s_t) d\mu(Q_t) \tag{2.9}$$

where $d\mu(Q_t)$ is a probability measure of Q_t. To derive an analytic solution, assume that

Q_t is a stochastic function of R_t given by

$$Q_t(R_t) = \begin{cases} \bar{Q}_t \equiv \mu R_t + \sigma\sqrt{R_t} & \text{with probability } 1/2 \\ \underline{Q}_t \equiv \mu R_t - \sigma\sqrt{R_t} & \text{with probability } 1/2. \end{cases} \tag{2.10}$$

Thus, Q_t is an *iid* random variable with mean μR_t and standard deviation $\sigma\sqrt{R_t}$. This functional form is chosen so that Q_t has the property of the law of large numbers, i.e. as R_t increases, the relative demand volatility—standard deviation divided by mean (known as a coefficient of variation)—declines by the factor of $\sqrt{R_t}$.

Then the expected profit (2.9) can be rewritten as

$$\mathbb{E}\pi_t = \alpha\mu R_t - c_s(s_t) - \frac{1}{2}c_p(\mu R_t + \sigma\sqrt{R_t} - s_t). \tag{2.11}$$

2.3.1. Baseline Case of No Reputation Concern

To consider the firm's choice of salaried labor s_t in the baseline case of no reputation building, suppose that there is no reputation and the firm wants to find s_t that maximizes expected profit (2.11). With discrete stochastic demand, I have to consider each possible region for optimal s_t^* relative to possible values of Q_t. To simplify the analysis, I assume that marginal cost of piece-rate labor is higher than marginal cost of salaried labor. This immediately restricts s_t^* to lie between the two possible values of Q_t for two reasons. First, there is no reason for the firm to hire more salaried labor than the maximum possible quantity of demand. Second, if $s_t^* < \underline{Q}_t$, the firm always has to hire piece-rate labor whose marginal cost is greater by assumption. Moreover, this is a reasonable assumption since temporary labor is less productive or lacks firm-specific skills due to shorter tenure, requiring more training. The search cost for temporary labor is also likely higher. The first-order condition is $\mathbb{E}\pi_t'(s_t^*) = 0$, i.e.

$$c_s'(s_t) = \frac{1}{2}c_p'(\mu R_t + \sigma\sqrt{R_t} - s_t). \tag{2.12}$$

The condition (2.12) shows that the optimal s_t equates the marginal cost of salaried labor, which is non-stochastic and thus known precisely, with the *expected* marginal cost of piece-rate paid labor. If one hires more salaried labor, the expected marginal savings from not having to hire more expensive piece-rate labor increases. However, at a sufficiently high s_t, the marginal cost of maintaining a salaried labor capacity becomes high enough to exceed the expected marginal cost of piece-rate labor.

How does demand volatility σ affect firms' relative use of piece-rate labor? Without reputation concern, the firm would only want to minimize the sum of expected labor costs for salaried and piece-rate labor. Since the firm hires piece-rate labor only when the demand turns out high, one can expect that an increase in the volatility σ may increase both salaried as well as piece-rate labor. This is expected given that they serve all the demand. Therefore, one should examine how the relative demand for piece-rate labor changes. Indeed I find that the firm increases the relative use of piece-rate labor as demand volatility increases unless the rate of increase in the marginal cost for that labor is too high relatively. This result is shown in Proposition 1. The proof is found in Appendix 2.9.

Proposition 1. *Suppose that there is no reputation consequence from firms' labor mix choice. Then when demand volatility increases, the firm's share of piece-rate labor increases under the assumption that piece-rate labor does not become "too expensive."*

2.3.2. Case of Reputation Concern

Now to understand the firms' optimal labor mix under reputation concerns, I first model the firm's reputation formation. I assume that quality signals φ_t are determined by the proportion of cases served by salaried nurses as follows:

$$\varphi_t \equiv \varphi\left(\frac{s_t}{Q_t}\right) = \frac{s_t}{AQ_t},$$

where A is the market average of quality signals, which is the mean proportions of salaried nurses in the market and thus lies between 0 and 1, inclusive. Furthermore, I assume the formation of reputation in (2.4) follows the law of motion given by a Cobb-Douglas function

$$R_{t+1} = R_t^{1-\gamma}\left(\frac{s_t}{AQ_t}\right)^{\gamma}. \tag{2.13}$$

A reputation value of 1 corresponds to the market average A in terms of quality signals. I assume the firm's initial reputation is below average, that is $R_0 < 1$. Furthermore, note that R_t is bounded above by $\frac{1}{A}$ for all time. For R_{t+1} is a weighted geometric average of R_t and $s/(AQ) \leqslant 1/A$. So if $R_t \leqslant \frac{1}{A}$, then also $R_{t+1} \leqslant \frac{1}{A}$. Since we assumed $R_0 < 1$, it follows by induction that $R_t \leqslant \frac{1}{A}$ for all t. This upper bound on reputation stock and consequently also quantity of demand guarantees compactness of the state space and justifies the use of stochastic Bellman theory.

(2.13) assumes that reputation in the next period is updated using a geometric mean of the current period's reputation and quality signals to allow for different weights placed on the history of reputation and quality signals. The smaller the weight γ on quality signals, the more "sticky" the firm's reputation is: the overall history of reputation is weighted more than just the quality signal from the last period.

Let $\beta \in (0,1)$ be a discount factor. By solving the Bellman equation in (2.8), I obtain the first-order condition given by

$$\mathbb{E}\left[\frac{\partial \pi_t}{\partial s_t} + \beta\frac{\partial R_{t+1}}{\partial s_t}V'(R_{t+1})\right] = 0, \tag{2.14}$$

and the envelope condition given by

$$V'(R_t) = \mathbb{E}\left[\frac{\partial \pi_t}{\partial R_t} + \beta\frac{\partial R_{t+1}}{\partial R_t}V'(R_{t+1})\right]. \tag{2.15}$$

Combining the first-order condition and the envelope condition and advancing one period forward, I obtain the Euler equation:

$$\mathbb{E}\frac{\partial \pi_t}{\partial s_t} = \beta \mathbb{E}\left(\frac{\partial R_{t+1}}{\partial s_t}\right)\left[\mathbb{E}\left(\frac{\partial \pi_{t+1}}{\partial s_{t+1}}\right)\frac{\mathbb{E}(\partial R_{t+2}/\partial R_{t+1})}{\mathbb{E}(\partial R_{t+2}/\partial s_{t+1})} - \mathbb{E}\frac{\partial \pi_{t+1}}{\partial R_{t+1}}\right] \tag{2.16}$$

The left-hand side of (2.16) represents the expected marginal profit from hiring one more unit of salaried labor in period t:

$$\mathbb{E}\frac{\partial \pi_t}{\partial s_t} = -c_s'(s_t) + \frac{1}{2}c_p'(\mu R_t + \sigma\sqrt{R_t} - s_t) < 0. \tag{2.17}$$

I assert that the sign of this expected marginal profit is negative for each t. It is not zero when there is a reputation concern (i.e. right-hand side of (2.16) is nonzero). Moreover, if it is positive, the firm always prefers to increase salaried labor because it increases both the short-term profit and reputation, therefore facing no trade-off. Therefore, when there is a reputation concern, increasing salaried labor reduces the firms' short-term profit. Note that this result can be compared with the case of having no reputation building where $\mathbb{E}\pi_t'(s_t^*) = 0$ is optimal.

On the right-hand side of (2.16), the factor

$$\mathbb{E}\left(\frac{\partial R_{t+1}}{\partial s_t}\right) = \frac{1}{2}\frac{\gamma}{A}\left(\frac{AR_t}{s_t}\right)^{1-\gamma}(\bar{Q}_t(R_t)^{-\gamma} + \underline{Q}_t(R_t)^{-\gamma}) > 0 \tag{2.18}$$

is the reputation gain in the next period from increasing one unit of salaried labor in period t. This scale is multiplied to the present discounted value of both future marginal profits from increasing salaried labor (in the first term) and from increasing reputation (in the second term) in the next period $t+1$ in the brackets. The first term in the brackets is a product of two quantities: expected marginal profit per unit of increase in salaried labor in the next period $t+1$, and the marginal reputation gain two periods in the future $t+2$ from increasing $t+1$'s reputation relative to the gain from new quality signals in $t+1$. The ratio measures a return on increasing salaried labor in t—how much the elevated base reputation stock contributes to the future reputation in period $t+2$ relative to new quality signals.

The second term in the brackets on the right-hand side of (2.16) represents the expected marginal profit in the next period from increased reputation:

$$\mathbb{E}\frac{\partial \pi_{t+1}}{\partial R_{t+1}} = \alpha\mu - \frac{1}{2}c_p'(\mu R_{t+1} + \sigma\sqrt{R_{t+1}} - s_{t+1})\left(\mu + \frac{\sigma}{2\sqrt{R_{t+1}}}\right) \tag{2.19}$$

Assume that parameters are set so that this expected derivative is positive, i.e. increasing future reputation enhances future profit. Taken all together, (2.16) shows that the higher expected marginal profit gains are from raising the reputation in the next period, the greater the short-term profit loss the firm is willing to endure and the more salaried labor it is willing to hire in the current period.

How do firms configure their labor mix in response to demand volatility when their reputations are at stake? As the firm's reputation becomes high, the short-term marginal profit loss from increasing salaried labor declines in (2.17). On the other hand, the marginal profit gain from increased reputation when the firm hires one more unit of salaried labor also seems to decline in (2.19). Therefore, for the firm with higher reputation, it may be more profitable to decrease the relative use of salaried labor.

To pin down exactly the role of demand volatility σ and reputation R_t in (2.16), I differentiate (2.16) with respect to σ and examine how it depends on R_t. Suppose that σ increases by one unit in period t but not in the future periods. According to the timing of the model, a change in σ in period t affects Q_t and thus s_t, which consequently affects future reputation R_{t+1} and thus s_{t+1}; however, it does not affect R_t. I find that the above intuition holds: the firm's relative use of salaried labor decreases with demand volatility if the reputation is higher. This result is shown in Proposition 2. The proof is found in Appendix 2.9. I find the reason for this is that the rate of increase in marginal profit from increasing reputation falls faster.

Proposition 2. *Firms decrease the share of salaried labor when demand volatility increases if their reputation is higher. Conversely, the firm's share of salaried labor increases with demand volatility if the reputation is lower.*

2.3.3. Summary

The model makes the following testable predictions:

(i) *When firms' reputation is lower, higher demand volatility decreases firms' share of piece-rate paid labor and increases firms' share of salaried labor.*

(ii) *When firms' reputation is higher, higher demand volatility increases firms' share of piece-rate paid labor and decreases firms' share of salaried labor.*

2.4. Data

My primary data source is rich proprietary data from a large US for-profit freestanding home health provider firm operating 106 autonomous offices in 18 states, which contain firms' labor configuration and patients' outcomes in each office at an unusual level of detail.[4] Since each office autonomously decides scheduling and staffing and is run as a profit center, it is regarded as a separate firm in the empirical analysis.[5] The data cover years 2012–2015.

My data contain the entire home health visit records in each office showing all the interactions between a patient and individual providers who served her. I match these visit-level data with the human resources data containing the history of employment arrangements for each provider. Thus, I can construct weekly panel data for firms showing demand and labor supply characteristics at the firm-week level. On the demand side, I can observe the

[4]These 18 states are Arizona, Colorado, Connecticut, Delaware, Florida, Hawaii, Massachusetts, Maryland, North Carolina, New Jersey, New Mexico, Ohio, Oklahoma, Pennsylvania, Rhode Island, Texas, Virgina, and Vermont.

[5]This large set of independently run offices alleviates some concern about the generalizability of our results to other HHAs even if they all belong to one company. During 2013, compared to a national sample of freestanding agencies, home health offices in our sample tend to be larger, have a lower share of visits provided for skilled nursing and instead have a higher share of visits provided for therapy, and have a lower share of episodes provided to dual-eligible Medicare or Medicaid beneficiaries, which seem to be more common characteristics of proprietary agencies (Cabin et al., 2014; MedPAC, 2016a).

number of ongoing episodes as well as construct the degree of demand volatility. An episode is defined as a 60-day period of receiving home health services, as described in Section A.1. On the labor demand side, I can measure the total number of active nurses in each work arrangement and firms' labor mix by computing the percentage of active nurses in each work arrangement. I can also compute the employee turnover rate by using HR data that contain employment start and termination dates for each worker. I define the turnover rate as the ratio of the number of nurses who terminate employment to the total number of nurses for each week.

Furthermore, my data provide referral sources for each patient, allowing me to track how many referrals come from each referral source, such as a hospital, for each firm-week cell. Using the referral source data, I compute various measures of reputation—defined as the establishment of strong referral network—as described in detail in Section 2.5.

I use firm-level data which provide each firm's address and start and end of business dates where the end of business date is available only for closed firms. Using the address information, I obtain the county of each firm by merging with external CMS data, such as the Provider of Services files and Medicare Cost Reports data. I also construct each firm's age (in years) using its start of business date information.

Finally, I use Medicare claims data I obtained from a private consulting company for selective years to obtain data on hospitals' referral patterns and market-level demand. First, I use 2012–2014 Medicare hospital claims data which identify the number of patients who are being discharged from each hospital and being referred to home health care. I then construct the total number of referrals to home health from each hospital in each week, and link the information with my patient referral data. Thus, I can measure the share of home health referrals coming from each hospital to each firm in my data every week. This referral share is then used to construct one of the reputation measures, as described in Section 2.5. Second, I use 2013–2014 Medicare home health claims data which provide the number of home health episodes in each Medicare-certified home health agency on each week. This count is aggregated to the county-week level so that I can create the county-week level demand volatility and market concentration index. These two variables are included as additional covariates in robustness check specifications.

For the main analysis, I construct firm-week level data where a week is chosen as the time unit of analysis because firms hire workers on a weekly basis. I use a period of weeks spanning from April 23, 2012 to November 9, 2015, the last week for which I have personnel data for the entire week.[6] Importantly, I restrict to the sample of "new in town" firms that had no previously existing branches in the firm's county, the unit of local market.[7] Since the firms in my data belong to one company, firms may get more brand recognition in the markets with previously existing branches. Furthermore, I restrict to firms that have been around for at most 8 years to keep the sample reasonably well balanced and avoid having too small sample size per firm.[8] Thus, my final sample includes 50 "new in town" firms in 15 states and contains 7,233 observations. 21 firms can be observed since their start of business.

2.5. Evolution of Firm's Demand Volatility, Reputation and Labor Mix: Descriptive Facts

To understand the role of firm reputation in determining firms' labor mix strategy, I begin with analyzing how the firms' reputation as well as demand environments change by firm age. Firm age is itself a source of reputation (Banerjee and Duflo, 2000) as well as its proxy. Thus, how each key variable changes with firm's age facilitates our understanding of how the relationship between labor mix and demand volatility changes with reputation.

I measure firms' reputation in several ways that represent the establishment of a strong

[6]The first few weeks in 2012 are dropped out since I construct many variables using the rolling mean or rolling standard deviation.

[7]To avoid counting firms that opened only just before a firm opened as incumbent, I define incumbent firms as having been around for at least 6 months at the time of a firm's opening.

[8]The number of firms that have been in business for more than 8 years substantially declines, and these firms are smaller in size even compared to new firms on average. Thus, these firms do not serve as a good control group when comparing with new firms.

patient referral network, as referrals are the primary way of generating new demand. Particularly, I focus on the size of a referral network, and dispersion, consistency, and share of referrals from hospitals. Hospitals are the largest referral source to home health agencies in my data; hospital referrals account for 30% of new admissions a week on average.

For each firm i and week t, I create the following four measures of reputation Rep_{it}. Higher value of reputation represents establishment of a stronger referral network. First, I measure the size of a referral network by counting the number of unique hospital referral sources that have referred to the firm i over the past 4 weeks including the current week, $t-3, ..., t$. Second, I measure the dispersion of referrals, which equals minus 1 times the Herfindahl-Hirschman index (HHI) of referrals among hospital referral sources over the previous 4 weeks. Thus, the higher and closer to zero the dispersion measure is, the more dispersed referrals are. The more dispersed referral network represents a stronger network since a firm does not depend on only a small set of hospitals to make referrals when the timing of patient's hospital discharge is idiosyncratic.

Third, I measure the consistency of referrals by computing the proportion of weeks a given hospital j has referred to the home health firm i repeatedly in the previous 4 weeks. I aggregate this firm-week-hospital level measure to the firm-week level by taking a weighted average. For the hospital weight ω_{ijt}, I use the share of total hospital referrals received by i over the past 4 weeks that come from each hospital j, assigning higher weights to hospitals that have referred relatively more to the firm recently.

Fourth, I measure the firm's share of referrals in each hospital, which represents the firm's importance as a referral partner to the hospitals. I compute the share of total Medicare patients being discharged from a hospital j to home health over the past 4 weeks that are referred to the home health firm i. This measures each firm i's relative importance as a referral partner to the hospital. Similar to the consistency measure above, I take a weighted average of this firm-week-hospital level measure using the same weights ω_{ijt}.

Figure 2 plots each of the four reputation measures for each firm-week against the firm age in years. The central line plots fitted values from a locally weighted regression (from the loess method) of each of the reputation measures on the continuous firm age values, and the outer lines plot point-wise confidence intervals. By all measures except the referral share, firms developed a stronger referral network of hospitals as they aged.[9] In Panel 2a, new firms received referrals from 3 different hospitals. However, over the course of their first 9 years, their network consistently grew and it included more than 10 different hospitals at age 8-9. As the network expanded, the dispersion of referrals naturally grew, as shown in Panel 2b. In Panel 2c, the referral consistency from the same hospital consistently grew as firms aged. The same hospital increasingly referred back to a firm with the probability of 60% when the firm is 8-9 years old, compared to 30% when the firm was new. However, the referral consistency did not rise further than 60% and leveled out after the age 3. In Panel 2d, the referral share from a hospital declined as firms aged. Hospitals decreased the share of home health agency referrals to the firms in my data as firms aged by nearly 10 percentage points when firms were 4 years old. This pattern is surprising as all the above three measures showed that the firms' reputation increased with firm age. However, the degree of decline is small compared to other measures of reputation.

As firms' reputation grew as they aged, how did their demand environments, and consequently their labor mix, change? Figure 3 shows that firms grew bigger and faced lower demand volatility as they aged. This is not surprising given that firms developed a stronger referral network as they aged, as shown in Figure 2. I measure demand in Panel 3a by the number of home health cases (i.e. 60-day episodes) served by the firm on a given week, which includes both new patients and patients whose care is extended for additional home health care. To measure the degree of demand volatility in Panel 3b, I use a type of volatility measure that is frequently used in the finance literature (Ferson, 2013). I first compute

[9] The reputation growth of firms shown in Figure 2 is comparable to other similar firm growth patterns noted in previous literature (Dunne et al., 1989; Haltiwanger et al., 1999; Oi and Idson, 1999; Brown and Medoff, 2003). The firm age has been found to be positively associated with firm productivity (Haltiwanger et al., 1999) and the likelihood of survival (Dunne et al., 1989). There are mixed results on the relationship between firm age and wage (Oi and Idson, 1999; Brown and Medoff, 2003).

the log ratio of the aforementioned demand for the current week to demand for the previous week, which approximates the week-to-week percentage change in demand volume. Then I take a standard deviation of these weekly log ratios over the past 4 weeks.[10][11] Even within each firm age year bin, there is a wider variation in demand volatility for younger firms than for older firms, as shown in Panel 3c. This figure shows the boxplot of mean demand volatility for each firm in each age year bin. Even if each data point is an aggregated mean for each firm in each age bin, the interquartile range (IQR) is greatest at firm age 0-12 months, and substantially declines once the firm reaches age 3.

How did firms' labor mix change as they aged? Figure 4 shows the weekly percentage of nurses hired in each arrangement by firm age.[12] For the sake of clarity, I grouped firm age into 4 different bins: 0-12 months old, 12-24 months old, 24-48 months old, and 48 or more months old (corresponding to firm age year 0, 1, 2-3, and 4 or more, respectively, in the previous figures). Older firms concentrated more on full-time and on-call nurses instead of using part-time, contract or office/other nurses. In particular, firms increased the percentage of nurses in full-time positions—the primary arrangement used for permanent employees—by nearly twofold from nearly 19% to 39%, when they were 4 or more years old compared to their inception. At the same time, they slightly decreased the percentage of on-call nurses—the primary arrangement used for temporary employees—from 43% to 36%. The labor mix is obviously endogenously determined by the demand size and volatility. Therefore, the increase in full-time nurses and decrease in on-call nurses with firm age coincide with an increase in demand volume and a decrease in demand volatility shown in Figure 3.[13]

[10] When I use the window of 8 weeks, the values of demand fluctuations show little change.

[11] My measure of demand volatility is likely understated since I use an endogenous measure of demand—the number of home health cases chosen by each firm—rather than an exogenous measure of demand such as the actual number of home health cases that arrived at the firm, some of which could be rejected. The volume of rejected cases might also vary across firm age.

[12] This proportion measure of labor inputs using stocks rather than service flows or rate of utilization is preferred in this context since service flows for workers are fixed in advance (for example, salaried workers are expected to provide the pre-specified number of visits on each week), or workers' visit allocation across days are shaped by patients' needs and workers' availability rather than firms' decisions. Service flows may be preferred for measuring labor inputs if, for example, one wants to precisely measure firms' productivity conditional on operating (Braguinsky et al., 2015).

[13] It is the change in the correlation between demand volatility and labor mix that I aim to estimate, not the level of labor mix.

However, firms' labor mix is more instantly determined by the time-varying demand environments, especially since firms can instantly vary the number of temporary nurses they hire. Therefore, the aggregate level of labor mix in Figure 4 fails to capture how firms' labor mix changes in response to demand volatility and whether the responses vary by firm age. Thus, in Figure 5, I examine how the slopes from the regression of the percentage of full-time nurses on demand volatility vary by firm age bin. Although firms of all ages decreased the percentage of full-time nurses as demand volatility increased (i.e. the sign of slopes is all negative), the slope is smallest for youngest firms aged 0-12 months in absolute value. Then the slope becomes steeper as firms age until they are 4 years old. However, the slope increases (in absolute values) stop once firms reach age 4 or more: these oldest firms behave more like the youngest firms in their labor mix responses. This reversal can be explained by low levels of demand volatility or the leveling out in determinants of the labor mix, such as the strength of referral network, demand size, and demand volatility.

The analysis above shows that firms' labor mix responses to demand volatility systematically varied by firm age, a proxy of firm reputation. In particular, firms of all ages decreased the percentage of full-time nurses with demand volatility but the extent of decrease was smaller among younger firms. However, is the systematic difference across firm ages in the relationships between the percentage of full-time nurses and demand volatility actually driven by firms' reputation among referral sources? The extent to which young firms can downsize the full-time workforce in response to higher demand volatility might be more limited for different reasons. For example, there might be a minimum necessary number of full-time nurses for the business operation, such as if firms need full-time nurses with good knowledge of designing care plans and documenting cases, or to manage temporary nurses. Then young firms that are small would respond to demand volatility by decreasing the percentage of full-time nurses by a smaller amount, as shown in Figure 5. Moreover, as shown in previous figures, not only the measures of reputation but also demand environments substantially changed as firms aged. Therefore, for a rigorous test of the model's predictions, in the next section, I present and estimate an econometric model controlling for other covariates that determine firms' labor mix.

2.6. Empirical Analysis

2.6.1. Empirical Specification

Using the main specification below, I investigate how firms' reputation among the referral sources is related to firms' labor mix responses to demand volatility. I look at changes in the percentage of full-time nurses within a firm in response to an increase in demand volatility, and use interaction terms between demand volatility and measures of firm reputation. The estimating equations are of the form

$$y_{it} = \beta + \gamma \cdot DV_{it} + DV_{it} \cdot \mathbf{Rep'}_{it} \cdot \boldsymbol{\theta} + \mathbf{Rep'}_{it} \cdot \boldsymbol{\delta} + \alpha_i + \mu_t + \mathbf{X'}_{it} \cdot \boldsymbol{\eta} + \epsilon_{it}, \tag{2.20}$$

where y_{it} is the percentage of active full-time nurses in firm i on week t. The key right-hand-side variables are a measure of demand volatility, DV_{it}, and interaction of the demand volatility with a vector of different reputation measures, $\mathbf{Rep}_{it}$, as described in Section 2.5. Since I want to look at changes within firms, I include firm fixed effects α_i, which allow me to control for potential geography-specific market or legislative factors and differences in time-constant management styles across firms. I also include week-year fixed effects μ_t to control for any industry-wide shifts in or seasonal effects on the labor mix. In the vector $\mathbf{X}_{it}$, I include other firm-week level covariates, such as 7 indicators for firm age year bins (omitted category is the indicator for the firm's first year) or log firm age, log of total demand volume, log of total active nursing workforce size, and the turnover rate among full-time nurses.[14]

To facilitate the interpretation of interaction term coefficients, I nonparametrically estimate the equation (2.20) using two quantile indicator variables for having 33-66th percentile ("high") values or 66-100th percentile ("very high") values of each reputation measure

[14]The turnover rate is measured by a ratio of the number of full-time nurses leaving the workforce to the total number of active nurses for each firm-week.

(omitted category is the lowest quantile for smallest values). For each reputation measure, I use quantile cutoffs based on the firm-specific distribution of all weeks within each one-year firm age bin.[15] The coefficients $\boldsymbol{\theta}$ are identified from changes in the correlation between the labor mix and demand volatility during weeks when a firm has particularly high reputation given the firm age, compared to weeks when a firm has low reputation. The coefficients $\boldsymbol{\theta}$ will reflect how the correlations between the percentage of full-time nurses and demand volatility change when each of different measures of reputation increases to "high" or "very high" values. The key coefficient γ of our interest will reflect the correlation between the percentage of full-time nurses and demand volatility when firms have low values of reputation by all measures.

In Table 7, I provide summary statistics for the variables included in the regression.

2.6.2. Results on the Effects of Reputation on Firms' Labor Mix Responses to Demand Volatility

I investigate whether firms' labor mix strategy in response to demand volatility systematically changes by their reputation among referral sources. Table 8 shows the results from estimating the within-firm specification in (2.20) while controlling for a different combination of four reputation measures described in Section 2.5: 1) referral network size (i.e. the total number of hospital referral sources); 2) dispersion of referrals; 3) referral consistency; and 4) referral share (i.e. mean share of total home health referrals from each hospital). Since the referral share data are available only for the years 2012–2014, specifications including this reputation measure are estimated on this subsample. I begin with including only one reputation measure at a time and include additional reputation measures to examine whether firms respond differently to a change in different measures of reputation.

Table 8 shows consistently that firms' percentage of full-time nurses was different when they had low and high levels of reputation. When firms were in the bottom third of reputation

[15] I create different cutoffs for each firm age bin to adjust for different ranges in the reputation measures across firm ages, as shown in Figure 2, and allow for comparing the effects of reputation across firms of similar tenure.

levels in the firm age-year specific distribution by any measures, they had a higher percentage of full-time nurses when demand volatility increased. In the first row, the positive association between the percentage of full-time nurses and demand volatility is statistically significant at the 5 percent level in all columns except columns (2) and (5). The correlation tends to be particularly stronger when more than one reputation measure is included, suggesting that different measures of reputation add up to each other in determining the overall level of reputation from the firms' perspective. Including a referral share using the subsample period of 2012–2014 also yields stronger correlation. For example, when firms had only a small referral network, the coefficient on demand volatility is 20.89 in column (1). But when firms had both small referral network and low referral consistency in column (6), the coefficient on demand volatility increases to 27.55. The coefficient declines slightly to 25.47 when firms also had low referral dispersion on top of these two variables in column (11) but rises again to 33.97 when firms also received a low referral share in column (13). The magnitudes implied by the coefficients are small, however, since demand volatility ranges from 0 to around 1. Firms with low reputation by all measures hired about 0.8-1.4 percentage-point or 2-4 percent more full-time nurses when demand volatility increased by one standard deviation (0.04).[16] This is translated to 0.2 to 0.3 more full-time nurse in an average firm that hired 21 nurses per week in total.

On the other hand, firms had a lower percentage of full-time nurses when reputation increased by any one of the measures, as shown by the negative coefficients on interaction terms. The negative coefficients on interaction terms are usually statistically significant only when reputation was higher in terms of referral network size and referral consistency, and are more likely to be significant for the top quantile indicators for each of the reputation measures. When firms had a top third size of referral network in the firm age-year specific distribution in column (1), the positive association between the percentage of full-time nurses and demand volatility is canceled out. When firms had a very large referral

[16] 2-4 percent increase is obtained by multiplying the estimated coefficients by the standard deviation of demand volatility, 0.04, times 100, divided by the mean percentage of full-time nurses, 34 percent.

network but had low referral consistency and received a low referral share in column (13), the percentage of full-time nurses was 2 percent higher when demand volatility increased by one standard deviation, as opposed to 4 percent higher when firms also had a small referral network. However, the positive association is canceled out again when firms had both a very large network and very high referral consistency even though firms still received a low referral share.

The main results from the above show that firms with lower reputation than expected for those in the firm age-year hired more full-time nurses in response to higher demand volatility than firms with higher reputation. However, did younger firms behave differently from older firms? Figure 2 shows that reputation increased with firm age. Do the results in Table 8 hold regardless of firm age and levels of reputation? The theory in Section 2.3 predicts that firms with lower levels of reputation—i.e. younger firms—increase the percentage of full-time nurses by even more than firms with higher levels of reputation. To investigate this, I separately estimate the equation (2.20) for firms in different age bins. I divide firm-week observations into three groups by firm age: 1) firms aged 0–12 months; 2) firms aged 12–48 months; and 3) firms aged 48 or more months. I replace the firm age year indicators with a continuous log firm age variable. Findings in Table 8 suggest that referral network size and referral consistency are measures of reputation to which firms were most sensitive. Thus, I focus on the specifications with these two measures of reputation in the next analyses. The full sample also ensures a large sample size for statistical power while the results were qualitatively similar, and yields rather conservative estimates.

In Table 9, it is only the youngest firms aged 0–12 months in columns (1)–(3) that had statistically significant positive associations between the percentage of full-time nurses and demand volatility when firms had a small referral network and low referral consistency. When demand volatility increased by one standard deviation (0.08), young firms with a small referral network had a 4 percentage-point or 17 percent higher percentage of full-time nurses compared to the mean percentage of full-time nurses at 25.62 percent according to column (1). From column (2), young firms with low referral consistency had a 6 percentage-point or 23 percent higher percentage of full-time nurses. From column (3), young firms with both small referral network and low referral consistency also had a 6 percentage-point or 24 percent higher percentage of full-time nurses. These results suggest having around 0.5-1 more full-time nurses given the mean total workforce size of 13 nurses among these young firms.

For older firms aged 12–48 months or more than 48 months, they had positive associations between the percentage of full-time nurses and demand volatility when having the bottom third of a reputation distribution. However, these associations are not statistically significant at the 10 percent level.

Moreover, it is only the youngest firms aged 0–12 months that had a statistically significant negative interaction term with a reputation measure, and the significant association appears only when the reputation is measured by referral consistency in columns (2) and (3). Column (2) shows that when young firms had high referral consistency, they had a 6 percent higher percentage of full-time nurses, as opposed to 23 percent, when demand volatility increased by one standard deviation. When young firms had very high referral consistency, they even had a slightly lower percentage of full-time nurses by 0.7 percent when demand volatility increased by one standard deviation. In comparison, results for older firms show that interaction coefficients have opposite signs and also are not precisely estimated even though the sample sizes are greater. Reputation may not be the most important driver of firms' labor mix responses for these older firms. Thus, findings in Table 8 are primarily driven by young firms in my data, which reinforce my model's predictions.

How did firms adjust their nursing workforce hired in other employment arrangements beyond full-time nurses? Since the percentage of nurses in each work arrangement sums up to 100 percent, an increase in the percentage of full-time nurses must accompany a decrease in the percentage of other nurses when firms had low reputation. However, which other work arrangement did firms adjust the most when they had low reputation? Did they differentially treat directly hired on-call nurses and independently contracted nurses? I investigate firms' heterogeneous responses to demand volatility across work arrangements. I estimate the equation (2.20) among the youngest firms aged 0–12 months using the percentage of active nurses hired in each arrangement as the dependent variable. For reputation measures, I include both referral network size and referral consistency.

In Table 10, I present columns in a descending order of organizational attachment of the arrangements (except the "Office/Other" category in column (6) representing office or other employees whose primary duty is not to visit patients). Column (1) reports the same results as in column (3) of Table 9 for full-time nurses while columns (2)–(6) show the results for nurses hired in part-time with benefits, part-time without benefits, on-call, independent contractor, and office/other categories. In the first row, firms in the bottom third of both reputation distributions during the first year had a lower percentage of nurses in all positions except in full-time positions. However, the only statistically significant negative association appears for independently contracted nurses, who have the least organizational attachment, in column (5). When having both small referral network and low referral consistency, young firms had a 4 percentage-point or 28% lower percentage of contractor nurses when demand volatility increased by one standard deviation. This translates to hiring 0.5 fewer contractor nurses.

Other statistically significant labor mix responses are using more part-time nurses with benefits when firms had higher referral consistency despite having a small referral network; however, firms used fewer part-time nurses when having a very large referral network if they had low referral consistency. Moreover, firms used fewer office/other nurses when having a larger referral network if they had low referral consistency. These results suggest that firms did not view part-time nurses with benefits or office nurses as substitutes for full-time nurses. Furthermore, firms appear more sensitive to referral consistency as a measure of reputation, as indicated earlier.

2.7. Alternative Explanations and Robustness Checks

2.7.1. Refuting the Alternative Explanation by Firm Size

The above findings are consistent with my model's predictions that reputation changes firms' labor mix responses to demand volatility. Firms with lower reputation had a higher percentage of full-time nurses when demand volatility increased. However, firms with higher reputation had either no change in or even a lower percentage of full-time nurses when demand volatility increased. These results are driven by youngest firms aged 0–12 months which also had the lowest reputation by any measures. Furthermore, low-reputation firms simultaneously decreased the percentage of contractor nurses with demand volatility.

However, there is a potential concern that the effect of reputation found above could be driven by other factors. A plausible confounding factor is the firm size. Section 2.5 showed that younger firms not only had lower reputation but also were smaller on average. Smaller young firms may expect to grow in the future more rapidly. There could be unobserved information about their formation of relationships with more referral sources, which I cannot control for. If so, firms with lower reputation could be the small ones with greater expected growth which, simultaneously, would increase the percentage of full-time nurses. Moreover, smaller firms plausibly incur higher costs of attracting temporary nurses. They face higher demand volatility, which could create more unstable work schedules for temporary nurses. Smaller firms also may be capacity constrained and have a shortage of human resources staff who play an important role in recruiting temporary workers. If these were the cases, then young firms could respond to demand volatility by increasing full-time or other permanent nurses purely due to a smaller size. I control for contemporaneous demand and nursing workforce sizes on the right-hand side when estimating (2.20). However, to the extent that firms have unobserved information on the demand growth forecast and hiring costs, the coefficients γ on demand volatility and $\boldsymbol{\theta}$ on the interaction terms could be contaminated by the omitted variable bias.

To disentangle the role of reputation among referral sources from the effect of firm size, I indirectly test whether the effects of reputation among young firms in Table 9 are driven by small young firms or large young firms. If it is large young firms that drive the results, then I can rule out the alternative explanation by the firm size. In Table 11 I report the results from estimating (2.20) separately for small and large young firms in each firm age group shown in Table 9. Large firms are defined as those in each firm age year bin having their mean total demand volume during the age year above the median.[17] I include the referral network size and referral consistency as reputation measures.

In the first row, it is only the young large firms aged 0–12 months in column (2) that had a positive association between the percentage of full-time nurses and demand volatility when firms had both small referral network and low referral consistency. While the coefficient is positive for both small and large young firms, it nearly doubles in size and is statistically significant only for large young firms. When large young firms had both small referral network and low referral consistency, they had a 4 percentage-point or 14 percent higher percentage of full-time nurses when demand volatility increased by one standard deviation (0.05), compared to the mean percentage of full-time nurses at 27 percent. This translates to 0.6 more full-time nurses given the mean nursing workforce size of 16 nurses in these firms. However, when these firms had larger referral network or higher referral consistency, the association between the percentage of full-time nurses and demand volatility is positive and negative, respectively, and not statistically significant at the 10% level. Thus, it appears that large young firms increased the percentage of full-time nurses with demand volatility, regardless of their reputation levels. In summary, columns (1) and (2) show that the reputation effects I am capturing for young firms are not driven by the firm size effects.

Similarly, I examine whether small and large firms among older firms behaved differently from each other in columns (3)–(6). Although I do not find any statistically significant effects among old firms in Table 9, the effects might differ by the firm size. The oldest

[17] I define whether a firm is large separately for each firm age year bin since firms' size varies by age. Thus, one firm can be large in one age year and small in another age year.

firms, aged 48 or more months, seem to respond to demand volatility differently according to the size of referral network in columns (5) and (6) but these interaction terms are only weakly statistically significant.

2.7.2. Falsificateion Test by Comparing with "Not New in Town" Firms

I provide further evidence that firms' reputation among referral sources determines their labor mix responses to demand volatility by conducting a falsification test. In this test, I compare "new in town" firms, which have been my main sample for preceding analysis, with "not new in town" firms, defined as those that had previously existing branches in thecounty, the unit of a local market.[18] I expect to find no effects of reputation among "not new in town" firms since they would be less sensitive to the levels of reputation among referral sources. They can get more brand recognition through previously established branch firms and be more likely to be receive referrals even without improving quality (i.e. "piggybacking effect"). This effect would lead to a particularly salient difference in firms' labor mix when firms have low reputation. "Not new in town" firms would not necessarily have to increase the percentage of full-time nurses with demand volatility.

This falsification test might be ineffective to the extent that low-reputation firms in markets with previously existing branch firms try to internalize the reputation externality (i.e. "reputation externality" effect) (Jin and Leslie, 2009). "Not new in town" firms may be more concerned about keeping up the high quality level if the consequence of low quality signals is transmitted to the other firms in the same market. This concern will be greater in markets with more existing branch firms. If this effect prevails, "not new in town" firms could behave just like "new in town" firms.

To empirically test for the piggybacking effect and reputation externality effect, I reestimate (2.20) using the sample of all "not new in town" firms and report results in column (1) of

[18] It is possible to use different units of markets at different scopes—Hospital Referral Regions (HRRs), which define larger market areas, and Hospital Service Areas (HSAs), which define smaller market areas than counties. However, an HRR is too large, leaving too few firms that are new in the area. On the other hand, an HSA is too small and a firm's set of patients are usually contained in multiple HSAs, rendering it inappropriate as a local market for referrals from hospitals.

Table 12. I no longer find that firms had a statistically significant positive association between the percentage of full-time nurses with demand volatility when having a small referral network and low referral consistency. This contrasts with a statistically significantly positive association found among "new in town" firms in column (6) of Table 8. The statistically insignificant estimate supports the hypothesis of the piggybacking effect: "not new in town" firms do not have to adjust their labor mix to improve quality despite low reputation levels because there are non-quality channels through which to grow referral networks.

Although "not new in town" firms can piggyback on previously existing firms' reputation and do not have to shift their labor mix towards full-time nurses, there can also be a reputation externality effect. Did low-reputation firms in markets with more incumbent branch firms want to keep up the quality level so as not to tarnish the reputation of the others and internalize the reputation externality? To assess this possibility, I estimate the equation separately for firms in markets with only one previously existing firm and firms in markets with two to four previously existing firms. The results are presented in columns (2) and (3), respectively. Comparing the coefficients on the main effect of demand volatility in the first rows of columns (2) and (3) provides evidence for the reputation externality effect. In column (3), firms in markets with two or more existing firms had a statistically significantly higher percentage of full-time nurses with demand volatility when having a small referral network and low referral consistency. In contrast, in column (2), when firms had only one existing firm with no pressure to internalize the reputation externality, they had a smaller and statistically insignificant, positive association.

2.7.3. Robustness Checks

To check for robustness, I control for two additional variables incrementally, motivated by two potential hypotheses. First, I control for the time-varying local market-level demand fluctuations where market is defined to be the firm's county. Second, I control for the time-varying local home health market share concentration measured by the HHI at the county level.

The first control is motivated by the potential channel through which market-level fluctuations in demand affect firms' labor mix choice. Suppose that demand shocks are positively correlated across home health agencies in the market at a given time. With a positive cross-sectional correlation in demand, if the market gets a positive demand shock, a surge in demand for temporary workers at the same time would make it hard for each firm to hire them if the supply of temporary workers in the local labor market is inelastic. Thus, a market-level demand shock could simultaneously shift firms' labor mix towards hiring more full-time workers. I use Medicare claims data for years 2013–2014 to construct the county-week level demand volatility in the same method as I measure the firm-week level demand volatility.

The second control is included since home health market competitiveness could influence firms' labor mix through the effect on relative bargaining power of employers in the local labor market and thus on wages. In more concentrated home health markets, employers have greater monopsony power in the home health labor market, being able to set a lower wage rate than firms in more competitive labor markets (Manning, 2003; Matsudaira, 2014).[19] To measure local home health market concentration, I construct the HHI using the share of total episodes served by each Medicare-certified home health agency in each county-week cell.

In Table 13 I report results after estimating (2.20) including all possible combinations of referral network size and referral consistency as reputation measures. I restrict to the subsample period of 2013–2014 for which I have the market level demand volatility and concentration level available. With this subsample, the coefficients are less precisely estimated even if I control for the same set of covariates in columns (1), (4), and (7) as in previous tables. The main effect of demand volatility is no longer statistically significant

[19]Home health provider firms' monopsony power can be also influenced by the competitiveness of other markets, such as hospitals, if skilled nurses' main employment setting is not the home health care industry.

except in columns (1)–(3) when firms had a small referral network. However, it is reassuring that the results change little once additional controls—market-level demand volatility and market concentration—are included.

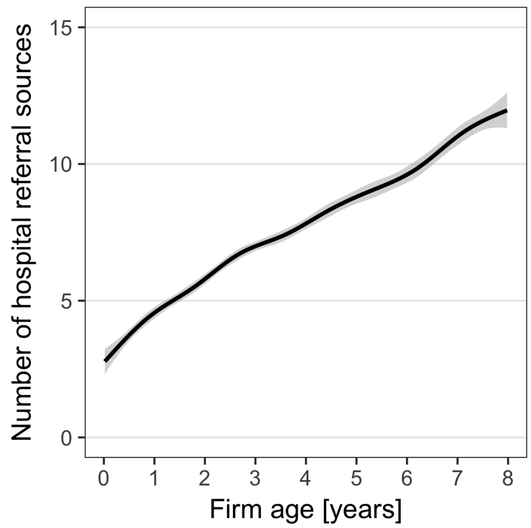
2.8. Conclusion

This chapter demonstrates that firms' reputation is an important determinant of labor mix in the face of demand fluctuations. I find that firms with lower reputation, especially younger firms, employ larger percentages of full-time nurses. This suggests that firms forgo short-term profitability in order to achieve long-term reputation through improvements in service quality. This hypothesis is further supported by evidence from Chapter 1 that patients visited by a higher proportion of full-time nurses were less likely to have a hospital readmission.

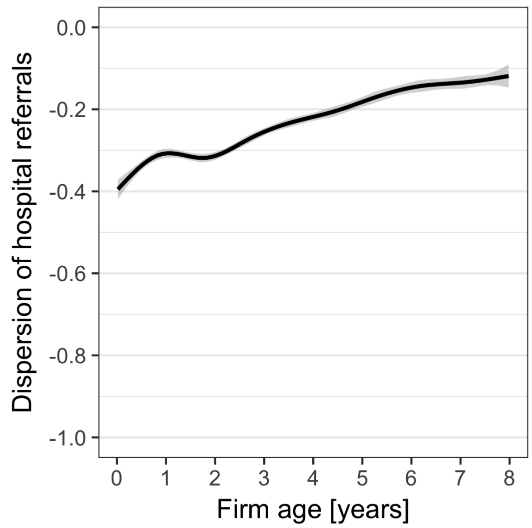
These observations have important implications for both industry and policy. First, for industry, this chapter shows that starting firms strategically adjust their labor mix in order to grow their reputation for quality and increase their referral base. Whether this is optimal for businesses and society would require a further examination of the endogenous increases in referral volume and improvement quality as a result of the firms' behaviors. This will be a fruitful avenue for future research. Second, although the home health market has been widely viewed as having low barriers to entry due to low capital requirements, this chapter points to a new barrier to entry since starting firms have to employ a higher share of permanent labor than more established firms.

Figure 2: Measures of Reputation by Firm Age

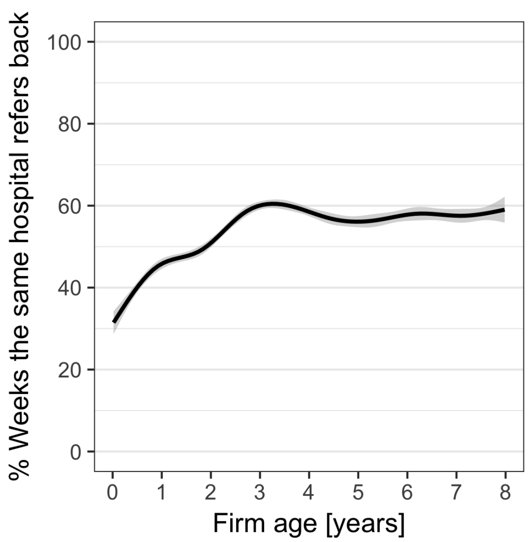
(a) Size of referral network



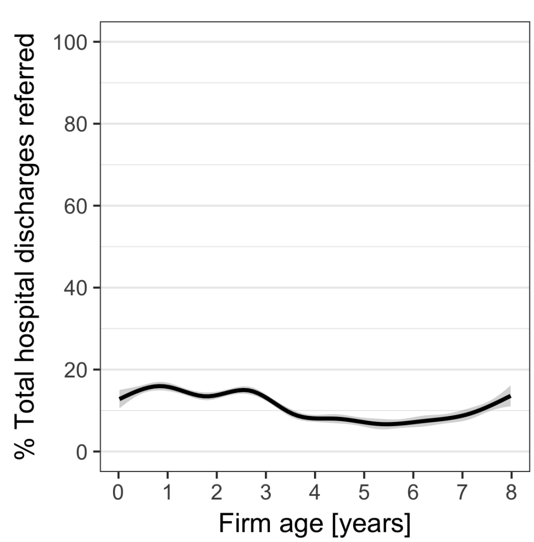
(b) Dispersion of referrals



(c) Consistency of referrals



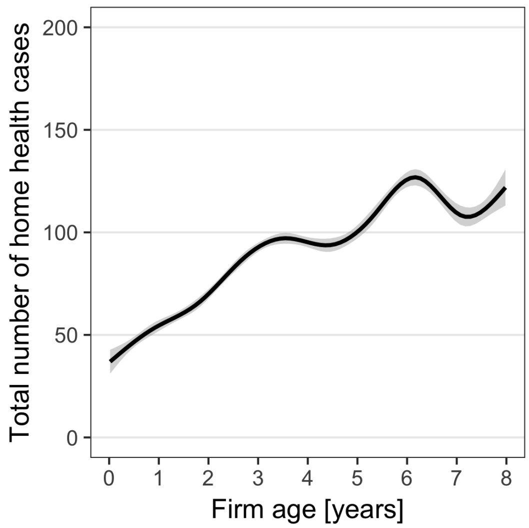
(d) Share of referrals from each hospital



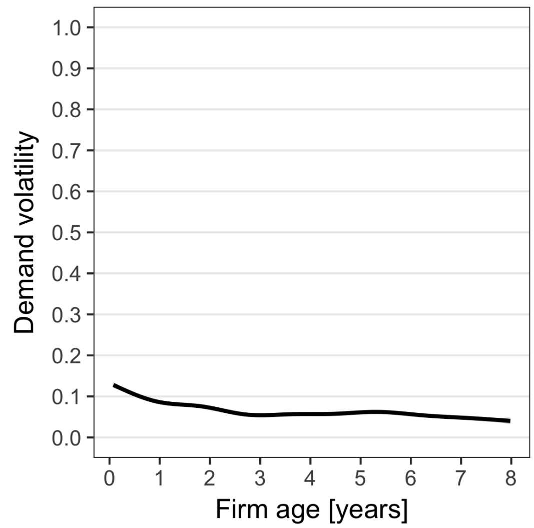
Notes: In each panel, the lines plot fitted values, along with point-wise 95-percent confidence intervals, of locally weighted regressions (using R's ggplot command with a geom smooth option) of each reputation measure on firm age in years at the firm-week level. The size of referral network in Panel (a) is measured by the number of unique hospital referral sources that has referred to a home health firm in the past 4 weeks, including the current week. The dispersion of referrals in Panel (b) is measured by minus 1 times the Herfindahl-Hirschman index (HHI) of referrals in the past 4 weeks. The consistency of referrals in Panel (c) is measured by the percentage of weeks referred by the same hospital referral source in the past 4 weeks. The share of referrals from each hospital in Panel (d) is measured by the percentage of home health referrals from a hospital made to the firm, aggregated across hospitals.

Figure 3: Demand Size and Volatility by Firm Age

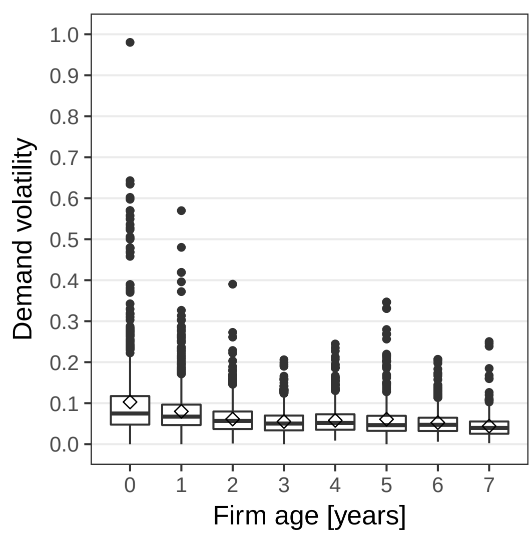
(a) Demand size



(b) Demand volatility

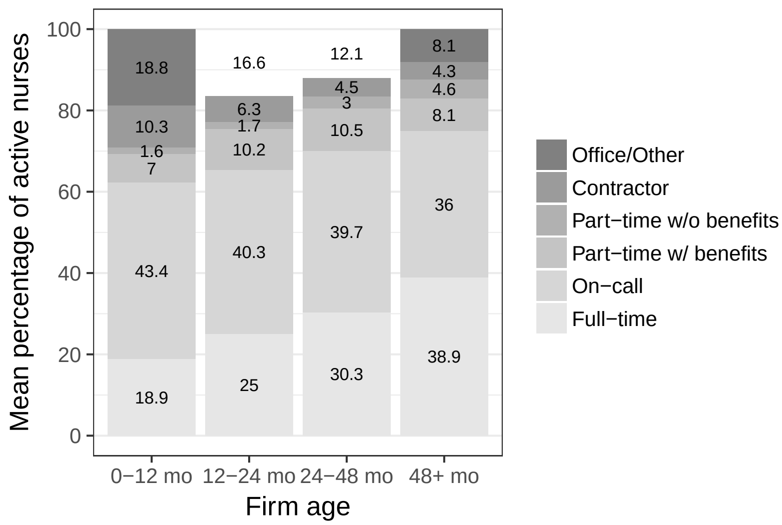


(c) Variation in demand volatility



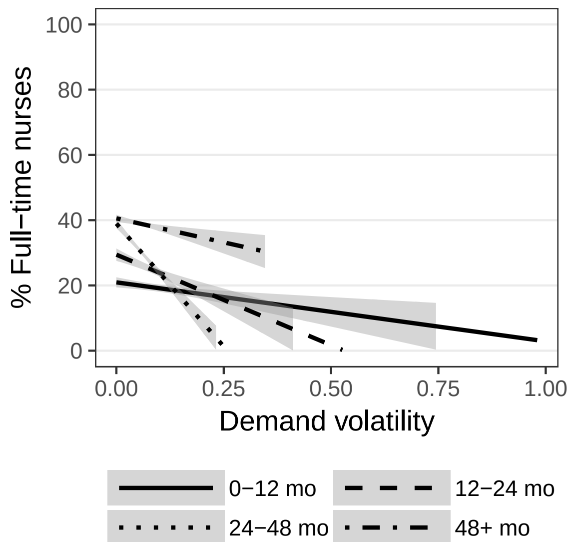
Notes: In Panels (a) and (b), the lines plot fitted values, along with point-wise 95-percent confidence intervals, of locally weighted regressions (using R's ggplot command with a geom smooth option) of each reputation measure on firm age in years at the firm-week level. Panel (c) shows box plots. I discretize continuous firm's age values to their floor values.

Figure 4: Labor Mix by Firm Age Bin



Notes: Weekly values for each variable are averaged in each firm's age bin for each firm.

Figure 5: Relationship between Demand Volatility and Percentage of Full-Time Nurses by Firm Age



Notes: The lines plot fitted curves, along with 95-percent confidence intervals, of linear regressions (using R's ggplot command with a geom smooth option)

Table 7: Summary Statistics

	All firms			Firms aged 0–12 months			Firms aged 12–48 months			Firms aged 48+ months		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Labor mix												
% full-time nurses	7,233	33.68	17.68	639	25.62	13.44	3,729	30.95	17.85	2,865	39.02	16.78
% part-time nurses with benefits	7,233	9.49	11.11	639	7.59	11.21	3,729	10.85	12.50	2,865	8.14	8.67
% part-time nurses without benefits	7,233	3.29	5.56	639	1.33	3.27	3,729	2.67	4.72	2,865	4.54	6.61
% on-call nurses	7,233	37.63	16.72	639	40.25	16.67	3,729	38.50	17.68	2,865	35.91	15.22
% contractor nurses	7,233	5.54	8.99	639	13.04	14.05	3,729	5.18	9.06	2,865	4.33	6.27
% office/other nurses	7,233	10.37	9.64	639	12.17	10.64	3,729	11.85	10.87	2,865	8.05	6.81
B. Demand volatility												
Firm demand volatility	7,233	0.06	0.04	639	0.09	0.08	3,729	0.06	0.04	2,865	0.05	0.04
C. Reputation												
Referral network size	7,233	9.09	5.48	639	4.70	2.78	3,729	7.38	4.42	2,865	12.31	5.49
Referral dispersion	7,233	-0.24	0.17	639	-0.33	0.21	3,729	-0.27	0.18	2,865	-0.16	0.10
Referral consistency	7,233	0.56	0.19	639	0.44	0.22	3,729	0.57	0.19	2,865	0.57	0.16
Referral share	5,503	0.17	0.24	622	0.20	0.33	2,897	0.21	0.28	1,984	0.12	0.11
D. Demand and labor supply characteristics												
Ln total number of ongoing episodes	7,233	4.52	0.69	639	3.95	0.66	3,729	4.39	0.61	2,865	4.81	0.67
Ln total number of active nurses	7,233	3.02	0.50	639	2.58	0.43	3,729	2.90	0.43	2,865	3.28	0.48
Full-time nurse turnover rate (%)	7,233	0.19	2.24	639	0.22	2.31	3,729	0.21	2.75	2,865	0.15	1.30
Ln firm age (years)	7,233	1.08	0.77	639	-0.73	0.62	3,729	0.88	0.36	2,865	1.73	0.21
E. Market characteristics												
Home health market demand volatility	3,344	0.05	0.05	231	0.05	0.03	1,897	0.05	0.06	1,216	0.05	0.05
Home health market concentration (HHI)	3,344	0.37	0.25	231	0.37	0.20	1,897	0.40	0.27	1,216	0.33	0.23

Notes. Number of observations, mean, and standard deviation are reported. Definitions of reputation are provided in Section 2.5.

Table 8: Effects of Reputation on Firms' Labor Mix Responses to Demand Volatility

	Dep var: Percentage of active full-time nurses													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Demand volatility (DV)	20.89**	11.84	22.10**	23.72***	16.89	27.55***	31.76***	25.07*	26.65**	28.33***	25.47*	28.17**	33.97***	31.96**
	(8.79)	(11.25)	(8.87)	(7.81)	(11.94)	(9.29)	(9.55)	(13.07)	(12.30)	(8.75)	(13.18)	(13.14)	(9.81)	(13.68)
Interaction with referral network size														
DV X Large referral network	-11.73				-11.67*	-9.20	-16.26				-7.35	-16.54*	-13.86	
	(7.80)				(6.74)	(8.17)	(10.02)				(7.73)	(8.69)	(9.89)	
DV X Very large referral network	-20.29**				-22.70***	-17.59*	-20.98**				-16.11*	-23.42**	-18.05*	
	(8.97)				(8.34)	(8.96)	(10.22)				(8.78)	(9.49)	(9.02)	
Interaction with referral dispersion														
DV X Dispersed referrals		6.56			12.96			6.70	3.22		11.34	9.98		5.14
		(13.58)			(13.02)			(12.45)	(12.69)		(12.31)	(12.12)		(11.61)
DV X Very dispersed referrals		-10.83			1.17			-15.58	-11.85		-5.97	1.80		-14.57
		(15.30)			(16.73)			(15.51)	(14.90)		(17.79)	(15.79)		(15.36)
Interaction with referral consistency														
DV X High referral consistency			-16.62**			-13.64		-18.55**		-12.58	-15.10*		-8.51	-13.43*
			(7.91)			(8.64)		(7.97)		(8.10)	(8.71)		(7.84)	(7.74)
DV X Very high referral consistency			-15.26*			-11.66		-19.35**		-21.02**	-14.58		-16.27*	-23.88**
			(8.31)			(8.14)		(9.18)		(9.75)	(9.43)		(8.13)	(10.17)
Interaction with referral share														
DV X Large referral share				-10.87			-7.26		-13.00*	-4.14		-7.21	-2.82	-6.05
				(7.62)			(9.14)		(7.74)	(8.23)		(8.86)	(8.93)	(8.06)
DV X Very large referral share				-13.84			-9.22		-16.27*	-3.46		-8.16	-1.86	-4.84
				(8.92)			(9.46)		(8.45)	(9.24)		(8.83)	(9.17)	(8.37)
Observations	7,233	7,233	7,233	5,503	7,233	7,233	5,503	7,233	5,503	5,503	7,233	5,503	5,503	5,503
R-squared	0.29	0.29	0.29	0.29	0.29	0.29	0.30	0.29	0.30	0.30	0.29	0.30	0.30	0.30
Office fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week-year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes. In all specifications, I control for 7 indicators for firm age year bins (omitted category is the indicator for the firm's first year), log of total demand volume, log of total active nursing workforce size, and the turnover rate among full-time nurses. In columns (4), (7), (9), (10), (12), (13) and (14), I use the sub-sample period of 2012–2014 due to limited data availability for the new reputation measure introduced in these columns. In the remaining columns, I use the full sample period of 2012–2015. Firm-level clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Effects of Reputation on Firms' Labor Mix Responses to Demand Volatility by Firm Age

	Dep var: Percentage of active full-time nurses								
Firm age	0-12 months			12-48 months			48+ months		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Demand volatility (DV)	53.63**	72.22***	76.68***	8.72	9.06	6.46	15.92	9.62	20.93
	(20.01)	(15.10)	(15.81)	(10.54)	(10.61)	(15.09)	(14.50)	(14.63)	(17.26)
Interaction with referral network size									
DV X Large referral network	-37.71		-9.38	-9.67		-9.64	-22.14		-22.01
	(24.56)		(37.48)	(13.09)		(12.90)	(17.88)		(17.85)
DV X Very large referral network	-40.15		-7.67	16.38		17.30	-25.79		-26.02
	(24.44)		(37.37)	(16.45)		(17.40)	(16.21)		(16.46)
Interaction with referral consistency									
DV X High referral consistency		-54.09**	-50.72		3.14	3.82		-13.58	-10.94
		(23.16)	(32.58)		(12.70)	(12.57)		(14.52)	(16.11)
DV X Very high referral consistency		-74.37***	-70.38*		1.78	4.35		-4.99	-7.80
		(22.11)	(34.57)		(13.05)	(13.83)		(13.54)	(13.79)
Observations	639	639	639	3,729	3,729	3,729	2,865	2,865	2,865
R-squared	0.42	0.42	0.44	0.32	0.32	0.32	0.41	0.41	0.42
Number of firms	21	21	21	37	37	37	34	34	34
Mean dependent variable	25.62	25.62	25.62	30.95	30.95	30.95	39.02	39.02	39.02
Office fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week-year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes. In all specifications, I control for log of firm age, log of total demand volume, log of total active nursing workforce size, and the turnover rate among full-time nurses. Firm-level clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Effects of Reputation on Firms' Labor Mix Responses to Demand Volatility among Young Firms Aged 0–12 Months

	Dep var: Percentage of active nurses in each arrangement					
	Full-time	Part-time with benefits	Part-time without benefits	On-call	Contractor	Office/ Other
	(1)	(2)	(3)	(4)	(5)	(6)
Demand volatility (DV)	76.68***	-10.85	-0.73	-15.77	-45.37***	-3.96
	(15.81)	(9.29)	(2.12)	(19.96)	(13.68)	(15.18)
<u>Interaction with referral network size</u>						
DV X Large referral network	-9.38	-17.37	-0.29	43.47	25.64	-42.08**
	(37.48)	(11.60)	(4.66)	(26.15)	(18.15)	(16.55)
DV X Very large referral network	-7.67	-23.58**	1.43	34.83	29.16	-34.18**
	(37.37)	(9.09)	(5.20)	(27.86)	(18.28)	(14.97)
<u>Interaction with referral consistency</u>						
DV X High referral consistency	-50.72	20.22*	-0.83	-24.59	23.01	32.91
	(32.58)	(9.91)	(3.06)	(32.41)	(16.92)	(24.72)
DV X Very high referral consistency	-70.38*	34.45***	-0.89	-10.99	4.38	43.42*
	(34.57)	(11.24)	(4.24)	(27.15)	(24.67)	(21.02)
Observations	639	639	639	639	639	639
R-squared	0.44	0.40	0.52	0.45	0.44	0.34
Mean dependent variable	25.62	7.59	1.33	40.25	13.04	12.17
Office fixed effects	Y	Y	Y	Y	Y	Y
Week-year fixed effects	Y	Y	Y	Y	Y	Y

Notes. In all specifications, I control for log of firm age, log of total demand volume, log of total active nursing workforce size, and the turnover rate among full-time nurses. In columns (1) and (2), I use the full sample period of 2012–2015. In columns (3) and (4), I use the sub-sample period of 2012–2014 due to limited data availability for the new reputation measure introduced in these columns. Firm-level clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Effects of Reputation on Firms' Labor Mix Responses to Demand Volatility by Firm Age and Firm Size

	Dep var: Percentage of active full-time nurses					
Firm age	0-12 months		12-48 months		48+ months	
Firm size	Small (1)	Large (2)	Small (3)	Large (4)	Small (5)	Large (6)
Demand volatility (DV)	41.18	77.06**	-4.93	20.39	14.11	13.93
	(34.12)	(25.73)	(23.34)	(20.31)	(20.49)	(14.25)
<u>Interaction with referral network size</u>						
DV X Large referral network	-72.37	26.27	4.11	-13.14	-15.08	-42.47*
	(55.00)	(69.39)	(18.34)	(27.75)	(24.22)	(23.19)
DV X Very large referral network	-58.83	21.44	13.57	41.38	-36.00*	-29.54
	(60.20)	(53.80)	(21.46)	(27.53)	(18.07)	(31.69)
<u>Interaction with referral consistency</u>						
DV X High referral consistency	17.12	-90.54	-1.43	-3.50	-13.98	11.18
	(42.28)	(55.26)	(16.38)	(21.86)	(19.63)	(10.17)
DV X Very high referral consistency	44.47	-81.16	-3.74	0.61	-8.53	-20.50
	(59.39)	(59.32)	(18.27)	(24.38)	(19.53)	(19.57)
Observations	181	458	1,780	1,949	1,320	1,545
R-squared	0.92	0.40	0.44	0.29	0.54	0.39
Number of firms	9	12	22	23	22	18
Mean dependent variable	22.09	27.01	22.89	38.32	33.06	44.12
Office fixed effects	Y	Y	Y	Y	Y	Y
Week-year fixed effects	Y	Y	Y	Y	Y	Y

Notes. In all specifications, I control for log of firm age, log of total demand volume, log of total active nursing workforce size, and the turnover rate among full-time nurses. Firm-level clustered standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12: Effects of Reputation on Firms' Labor Mix Responses to Demand Volatility among "Not New in Town" Firms

	Dep var: Percentage of active full-time nurses		
	(1)	(2)	(3)
	All	1 Existing firm	2+ Existing firms
Demand volatility (DV)	34.64	19.62	55.87**
	(19.47)	(25.94)	(12.93)
<u>Interaction with referral network size</u>			
DV X Large referral network	-26.95*	-18.57	-10.43
	(12.49)	(12.49)	(5.12)
DV X Very large referral network	3.46	49.06**	-18.86
	(22.49)	(15.32)	(19.51)
<u>Interaction with referral consistency</u>			
DV X High referral consistency	-22.39*	-15.22	-17.75
	(12.47)	(23.46)	(21.87)
DV X Very high referral consistency	-31.20*	-28.74	2.13
	(15.00)	(25.00)	(27.92)
Observations	1,595	1,248	347
R-squared	0.41	0.44	0.85
Number of firms	13	9	4
Mean dependent variable	38.91	39.21	37.82
Office fixed effects	Y	Y	Y
Week-year fixed effects	Y	Y	Y

Notes. In all specifications, I control for 7 indicators for firm age year bins (omitted category is the indicator for the firm's first year), log of total demand volume, log of total active nursing workforce size, and the turnover rate among full-time nurses. Firm-level clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Robustness Check with Market Condition Controls: Effects of Reputation on Firms' Labor Mix Responses to Demand Volatility

	Dep var: Percentage of active full-time nurses								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Demand volatility (DV)	25.03*	25.12*	24.49*	15.91	15.70	15.46	23.07	22.76	22.02
	(12.62)	(12.52)	(12.36)	(12.49)	(12.50)	(12.15)	(15.37)	(15.38)	(15.07)
Interaction with referral network size									
DV X Large referral network	-24.37*	-23.83*	-22.51*				-24.68*	-24.19*	-22.87*
	(12.52)	(12.54)	(12.71)				(12.73)	(12.78)	(12.98)
DV X Very large referral network	-4.99	-4.92	-3.83				-5.48	-5.59	-4.54
	(16.23)	(16.30)	(16.11)				(15.15)	(15.27)	(15.16)
Interaction with referral consistency									
DV X High referral consistency				2.26	3.11	3.34	3.11	3.95	4.00
				(11.87)	(11.97)	(11.85)	(11.10)	(11.20)	(11.16)
DV X Very high referral consistency				5.40	6.33	6.79	5.76	6.68	7.07
				(14.60)	(14.60)	(14.45)	(13.38)	(13.38)	(13.30)
Observations	3,344	3,344	3,344	3,344	3,344	3,344	3,344	3,344	3,344
R-squared	0.40	0.40	0.41	0.40	0.40	0.40	0.40	0.40	0.41
Mean dependent variable	33.06	33.06	33.06	33.06	33.06	33.06	33.06	33.06	33.06
Market level demand volatility		Y	Y		Y	Y		Y	Y
Home health market competition			Y			Y			Y
Office fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week-year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes. In all specifications, I control for 7 indicators for firm age year bins (omitted category is the indicator for the firm's first year), log of total demand volume, log of total active nursing workforce size, and the turnover rate among full-time nurses. I use the sub-sample period of 2013–2014 due to limited data availability on the market-level controls. Firm-level clustered standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Proof. (Proposition 1) I examine the effect of σ on p^* relative to the effect of σ on s^*. By total differentiation of (2.12), I obtain

$$\frac{\partial s_t^*}{\partial \sigma} = \frac{\frac{1}{2}c_p''(p_t^*)\sqrt{R_t}}{c_s''(s_t^*) + \frac{1}{2}c_p''(p_t^*)} \tag{2.21}$$

$$\frac{\partial p_t^*}{\partial \sigma} = \sqrt{R_t} - \frac{\partial s_t^*}{\partial \sigma} = \frac{c_s''(s_t^*)\sqrt{R_t}}{c_s''(s_t^*) + \frac{1}{2}c_p''(p_t^*)}. \tag{2.22}$$

Thus, when demand volatility σ increases, p^* increases faster than s^* if

$$\frac{\frac{\partial p_t^*}{\partial \sigma}}{\frac{\partial s_t^*}{\partial \sigma}} = \frac{c_s''(s_t^*)}{\frac{1}{2}c_p''(p_t^*)} > 1 \quad \text{or} \quad 2c_s''(s_t^*) > c_p''(p_t^*). \tag{2.23}$$

(2.23) shows that the firm increases piece-rate labor more than salaried labor in response to higher demand volatility unless the difference in the rates of increase in marginal costs of the two types of labor is very large. In this example, the rate of increase in the marginal cost of piece-rate labor has to be less than twice the rate of increase in the marginal cost of salaried labor by the construction of the stochastic distribution of demand. □

Proof. (Proposition 2) To simplify the analysis, I plug in (2.13) for the ratio on the right-hand side of (2.16) and obtain

$$M \equiv \frac{\mathbb{E}(\partial R_{t+2}/\partial R_{t+1})}{\mathbb{E}(\partial R_{t+2}/\partial s_{t+1})} = \frac{1-\gamma}{\gamma}\frac{s_{t+1}}{R_{t+1}} > 0. \tag{2.24}$$

I plug in (2.24) when differentiating the equation (2.16).

Furthermore, I assume convex labor cost functions as follows,

$$c_s(s_t) = \frac{1}{2}ax^2 \quad \text{and} \quad c_p(x) = \frac{1}{2}bx^2, \tag{2.25}$$

where $a < b$ is assumed since temporary labor is less productive or lacks firm-specific skills, requiring more training.

The derivative of the LHS of (2.16) with respect to σ is

$$\mathbb{E}\frac{d}{d\sigma}\pi_t'(s_t) = \mathbb{E}\pi_t''(s_t)\frac{ds_t}{d\sigma}. \tag{2.26}$$

The derivative of the first term before the brackets on the RHS of (2.16) with respect to σ is

$$\mathbb{E}\frac{d}{d\sigma}R_{t+1}'(s_t) = \mathbb{E}R_{t+1}''(s_t)\left(\frac{ds_t}{d\sigma} + \frac{dQ_t}{d\sigma}\right) = \mathbb{E}R_{t+1}''(s_t)\frac{ds_t}{d\sigma} \tag{2.27}$$

since $\mathbb{E}\frac{dQ_t}{d\sigma} = 0$. Let B denote the terms in the brackets on the RHS of (2.16):

$$B = \mathbb{E}\left(\frac{\partial \pi_{t+1}}{\partial s_{t+1}}\right)\frac{\mathbb{E}(\partial R_{t+2}/\partial R_{t+1})}{\mathbb{E}(\partial R_{t+2}/\partial s_{t+1})} - \mathbb{E}\frac{\partial \pi_{t+1}}{\partial R_{t+1}}. \tag{2.28}$$

After plugging (2.24) into (2.28), I obtain the derivative of B with respect to σ:

$$\begin{aligned}\frac{dB}{d\sigma} &= (s'_{t+1}(\sigma) + R'_{t+1}(\sigma))[\pi''_{t+1}(s_{t+1})M - \pi''_{t+1}(R_{t+1})] \\ &\quad + \mathbb{E}\frac{\partial \pi_{t+1}}{\partial s_{t+1}}\left(\frac{R'_{t+1}(\sigma)}{R_{t+1}}M + \frac{1-\gamma}{\gamma}\frac{s'_{t+1}(\sigma)}{R_{t+1}}\right).\end{aligned} \tag{2.29}$$

It follows from (2.13) that

$$R'_{t+1}(\sigma) = \frac{\gamma}{s_t}R_{t+1}s'_t(\sigma). \tag{2.30}$$

Using the results from (2.26), (2.27), (2.29), (2.30), total differentiation of (2.16) is given by

$$\mathbb{E}\pi''_t(s_t)\frac{ds_t}{d\sigma} = \beta\left[\mathbb{E}R''_{t+1}(s_t)\left(\frac{ds_t}{d\sigma}\right)B + \mathbb{E}\frac{\partial R_{t+1}}{\partial s_t}\frac{dB}{d\sigma}\right] \tag{2.31}$$

which can be rewritten, using (2.29), as

$$s'_t(\sigma) \equiv \frac{ds_t}{d\sigma} = \frac{\beta s'_{t+1}(\sigma)\left[\mathbb{E}R'_{t+1}(s_t)K + \frac{1-\gamma}{\gamma}\frac{\mathbb{E}\pi'_{t+1}(s_{t+1})}{R_{t+1}}\right]}{\mathbb{E}\pi''_t(s_t) - \beta\left[\mathbb{E}R''_{t+1}(s_t) + \frac{\gamma}{s_t}R_{t+1}\mathbb{E}R'_{t+1}(s_t)K + \frac{\gamma}{s_t}\mathbb{E}\pi'_{t+1}(s_{t+1})M\right]} \tag{2.32}$$

where

$$K = \mathbb{E}\pi''_{t+1}(s_{t+1})M - \pi''_{t+1}(R_{t+1}). \tag{2.33}$$

I show that the sign of $s'_t(\sigma)$ depends on R_t. Since the expression is rather unwieldy, I switch now to more heuristic arguments to determine the sign. First, I assume that $s'_t(\sigma)$ and $s'_{t+1}(\sigma)$ have the same sign. Second, in the numerator, I know from (2.17) and (2.18) that $\mathbb{E}R'_{t+1}(s_t) > 0$ and $\mathbb{E}\pi'_{t+1}(s_{t+1}) < 0$, respectively. Moreover, $(1-\gamma)/\gamma$, $R_{t+1} > 0$. To determine the sign of K, note that

$$\mathbb{E}\pi''_{t+1}(s_{t+1}) = -c''_s(s_{t+1}) - \frac{1}{2}c''_p(\mu R_{t+1} + \sigma\sqrt{R_{t+1}} - s_{t+1}) < 0, \tag{2.34}$$

and

$$\begin{aligned}\pi''_{t+1}(R_{t+1}) &= -\frac{1}{2}\bigg[c''_p(\mu R_{t+1} + \sigma\sqrt{R_{t+1}} - s_{t+1})\Big(\mu + \frac{\sigma}{2\sqrt{R_{t+1}}}\Big)^2 \\ &\quad - c'_p(\mu R_{t+1} + \sigma\sqrt{R_{t+1}} - s_{t+1})\frac{\sigma}{4R^{3/2}}\bigg] \\ &= -\frac{b}{2}\bigg[\mu^2 + \frac{\sigma}{4\sqrt{R_{t+1}}}(3\mu - \frac{s_{t+1}}{R_{t+1}})\bigg] \\ &< 0.\end{aligned} \tag{2.35}$$

Both results following from the convexity of the cost functions assumed in (2.25) and under the reasonable assumption that $3\mu R_{t+1} > s_{t+1}$. Since $M > 0$ from (2.24), there are conflicting signs in K; the sign of K depends on R_{t+1}. The fact that the second derivatives of cost functions are constants by construction implies that the first term of K in (2.33) becomes less negative when R_{t+1} gets large, since $M > 0$ gets smaller while $\mathbb{E}\pi''_{t+1}(s_{t+1}) < 0$ is constant. However, when R_{t+1} gets large, the second term $-\pi''_{t+1}(R_{t+1}) > 0$ of K in (2.33) increases in magnitude. Therefore, K becomes positive as R_{t+1} increases. Moreover, the second term in the brackets of the numerator in (2.32) becomes less negative as R_{t+1} increases. Therefore, the numerator becomes positive when the firm's reputation is sufficiently high.

Now in the denominator, note that

$$\mathbb{E}R''_{t+1}(s_t) = \frac{1}{2}\frac{\gamma}{A}(1-\gamma)\bigg(\frac{AR_{t+1}}{s_t}\bigg)^{-\gamma}(-s_t^{-2}) < 0,$$

and as R_{t+1} gets large, this quantity gets less negative since it declines in absolute magnitude. Furthermore, the sum of the second and last term becomes positive when the firm's reputation R_{t+1} is sufficiently high using the same argument as above. Therefore, the denominator becomes negative when the firm has higher reputation. Taken together, the sign of $s'_t(\sigma)$ becomes negative as the firm's reputation increases.

It is not necessary to separately examine the effect of σ on the share of salaried labor in this case. Recall that the firm hires piece-rate labor in my model only when the high value of demand is realized. Since that value increases as σ increases, and the firms always choose to serve all demand, a reduction in salaried labor must be matched by a corresponding increase of piece-rate labor.

To prove the converse—that the firm's share of salaried labor increases with demand volatility if the reputation is lower—one can use the same proof as above except now hypothesizing lower values of reputation R_{t+1}. □

CHAPTER 3 : The Effect of Workforce Assignment on Performance

3.1. Introduction

Workforce allocation and scheduling are routinely designed to achieve multiple organizational goals, with efficiency typically viewed as the leading objective.[1] Efficient workforce assignment entails the matching of task and talent (Garicano and Santos, 2004), management of planned and unplanned absences (Ehrenberg, 1970; Allen, 1983), exigency and geographical optimization, and responsiveness to demand shocks (Hamermesh and Pfann, 1996). Beyond efficiency, workforce allocation goals may include rewarding seniority, promoting workforce equity, and enabling effective learning and synergy (Mas and Moretti, 2009). These goals potentially compromise short-term efficiency but at the same time raise employee satisfaction and reduce costly turnover. Another set of objectives is linked with the use of workforce assignment to achieve higher quality. While often in conflict with cost minimization goals, higher quality may be rewarded directly through higher willingness to pay and indirectly through increased reputation.

Hospitals and health care systems implement strategies to improve the quality of care for all patients through focusing on patient safety, reducing medical errors, establishing evidence-based guidelines, and lowering the rate of unnecessary and preventable intervention (Kozak et al., 2001; Makary and Daniel, 2016). In fact, ensuring continuity of care within and across care settings is identified as a pillar of quality improvement (Richardson et al., 2001).[2] Continuity of care across settings involves, by definition, a multi-professional pathway that emphasizes the need for care coordination. On the other hand, continuity of care within a setting is achieved by workforce allocation, and in particular a continuous relationship between a patient and a single health care professional who is the sole source of care and information for the patient.

[1] This chapter is coauthored by Guy David.

[2] Continuity of care has also been shown to reduce utilization and costs of care (Raddish et al., 1999), such as by reducing the number of emergency department visits and shortening the length of hospital stays (Wasson et al., 1984).

However, the achievement of continuity of care requires costly deployment of resources. Ensuring smooth transitions in care and effective transmission of information between providers likely imposes massive constraints that interfere with the goal of optimizing scheduling to minimize workforce turnover and contractual disruptions. Thus, efficient workforce assignment may lead to reductions in quality of care through compromised care continuity. Using a novel data set from a large multi-state freestanding home health agency, this chapter quantifies the effect of within-setting care discontinuity caused by workforce assignment on hospital readmissions, a common quality of care marker.

Spending due to unplanned hospital readmissions was estimated at \$17.4-\$25 billion annually, which would translate to 16-22% of the total Medicare spending on inpatient hospital services (Pricewaterhouse Coopers' Health Research Institute, 2008; Jencks et al., 2009). The national all-cause potentially preventable readmission rates for this population was 11% in 2014 (MedPAC, 2016b). Starting in October 2012, the Center for Medicare and Medicaid Services (CMS) lowered its payment to hospitals with excess readmissions over the national average by up to 3%.[3] Facing financial penalties, hospitals use management strategies and modifications to their organizational structure to prevent hospital readmissions. For example, hospitals vertically integrated with post-acute care providers such as home health agencies (HHAs) to improve post-discharge care coordination, as increased reliance on home health has been shown to be associated with a reduction in hospital readmissions (Polsky et al., 2014).[4] Moreover, hospitals rely on post-acute care entities to reduce avoidable readmissions (Naylor et al., 2012). Once patients are discharged from hospitals, post-acute care providers monitor and treat still frail patients over an extended period of time.[5] Thus, post-acute care providers can impact the frequency of hospital readmissions

[3] The amount of reduction in payment was up to 1 percent in FY 2013, the first year of the HRRP, and up to 2 percent in FY 2014.

[4] Naylor et al. (1999) discuss hospitals that instituted programs to provide patient education before discharge, increased patient follow-up, and expanded the use of health information technology to track readmissions and integrate care across settings; Kim et al. (2015) show that admitting ER patients to the Intensive Care Units could substantially reduce hospital readmissions, and therefore suggest implementing admission criteria based on objective measures of patient risk as well as physicians' discretionary information as a promising way to decrease hospital readmissions.

[5] In the case of home health care, the default length of an episode is 60 days for Medicare patients.

by implementing workforce assignment strategies that promote care continuity.

We focus on home health care as it is an important and rapidly growing segment of the health care delivery system. Over the past decade, payment for home health services more than doubled (MedPAC, 2016a). This rapid growth may be attributed to its appeal to patients who prefer to recover at home, providers who prefer to shorten hospitalization lengths, and insurers who benefit from cheaper care at home than care in brick-and-mortar institutions. Home health care is recognized as a partial substitute for institutional long-term care (Guo et al., 2015). The importance of home health care has also increased with the rise of enhanced care coordination and shared savings models such as Accountable Care Organizations or Bundled Payments for Care Improvement (Sood et al., 2011).

Studying the intricacies of home health care provision and its impact on hospital readmissions is timely and important. Before the ACA, there was no competitive pressure for HHAs and no financial incentives to reduce readmissions, with three in ten post-acute home health stays resulting in a hospital readmission among Medicare patients (MedPAC, 2014).[6] However, with readmission penalties and the emphasis on population health management, home health has become a way to allow for continuity of care outside of the hospital and effectively manage the patient health to prevent unnecessary readmissions. Freestanding agencies often view the ability to mitigate hospital readmission as a key competitive differentiator in contracting with hospitals (Worth, 2014). Therefore, it is important to uncover potential mechanisms that lead to better care continuity and patient outcomes.

In this chapter, we use novel data containing over 43,000 home health patient episodes and spanning 89 autonomously run home health offices in 16 states. The data provide detailed information, which includes visit logs for all Medicare patients, work logs and human resources data for all home health providers, as well as all patient demographic and health risks collected as part of the Outcome and Assessment Information Set (OASIS) required by

[6]This figure could also be attributed to the fact that patients being discharged to home health care tend to be sicker and at a higher risk of hospital readmissions that those being discharged to home.

the CMS. In addition, our data are linked with individual patients' hospital readmissions. We measure care discontinuity by handoffs between skilled nurses over a patient's episode of care, which are immediately affected by offices' workforce allocation decisions.[7] We estimate a plausibly causal effect of provider handoffs on hospital readmissions using day-to-day human resources data on providers' absence, assignment to an alternative office, and job termination to instrument for handoffs. Unplanned employee absences in the US health care and social assistance sector consumed 1.9% of all scheduled work hours in 2016 (Bureau of Labor Statistics, 2017). To uncover the mechanisms underlying the effect of handoffs, we also examine whether the probability of readmission is affected by the frequency and sequencing of handoffs.

Estimating the effect of handoffs in home health care on the probability of readmissions raises endogeneity concerns. While we observe a great deal of patient characteristics as well as labor supply conditions, the data do not provide us with the actual care plan for each patient's episode of care. The care plan is plausibly linked to unobserved patient severity and hence to the risk of hospital readmissions. As we discuss in the chapter, it is challenging to determine the sign of the omitted variable bias caused by unobserved patient characteristics. To address this endogeneity problem, we use detailed provider-day level data on nurses' availability to instrument for both handoffs and the probability of receiving a visit. The instrument exploits the fact that skilled nurses' absence affects rehospitalization only through its effect on care discontinuity either through missed visits or handoffs. In addition, and as explained in greater detail in our methods section, we control for the dynamic changes in patients' health status during a home health episode by limiting the variation in our data to reflect the number of days since the last nurse visit; the mean interval of days between two consecutive nurse visits; the passage of time from the beginning of the episode; the relationship stock with various nurses during the episode; as well as supply and demand characteristics at the nurse and office level. Together with the patient's initial health assessment, these controls help mitigating potential confounding

[7] Skilled nurses refer to registered nurses (RNs) or licensed practical nurses (LPNs).

effects.

Using the cross-sectional variation, we find that patients experiencing nurse handoffs are 19% more likely to be readmitted to a hospital. This estimate more than doubles in magnitude when using the instrumental variables approach. Our results are robust to controlling for days since last visit as well as a rich set of patients' health risk, demographic, and comorbidity factors, office fixed effects, time fixed effects, and home health day fixed effects. Controlling for home health day fixed effects is especially important because the probabilities of hospital readmissions and handoffs rapidly decline over the course of a home health episode.

To explore potential mechanisms underlying this effect, we analyze finer partitions of handoffs by frequency and sequencing. We find the effect of first handoffs to have the strongest effect on increasing the likelihood of hospital readmissions, with the second and third handoffs having effects that are smaller in magnitude. The effect of having four or more handoffs is no longer statistically significant. Our finding that initial handoffs are more impactful than subsequent ones, controlling for elements of the patient episode dynamics, suggests that to effectively reducing hospital readmissions, it is important to ensure provider continuity throughout the entire episode of care.

A number of potential mechanisms may account for the effect of provider handoffs on hospital readmissions. First, information transmission between providers involved in a handoff may be incomplete and lead to potentially inappropriate care (Riesenberg et al., 2009). Second, holding the number of visits constant, handoffs lower the time spent with each individual provider, and hence depreciates the relationship stock built between providers and patients, which has been shown to improve patient outcomes (Saultz and Lochner, 2005). Third, repeated visits enhance the development of patient-specific knowledge, which has limited applicability to other patients. Therefore, patients experiencing a handoff lose access to providers most familiar with their case. For example, previous literature emphasizes the development of firm- or patient-specific skills among cardiac surgeons and radiologists, which are associated with a reduction in patient mortality rates (Huckman and Pisano, 2006). The three channels above serve as theoretical underpinning for our findings of a positive link between provider handoffs and hospital readmissions.

In summary, this chapter provides the first set of results linking care discontinuity in a post-acute care setting to increased risk of hospital readmissions. To date, most of the literature on care continuity has focused on transitions of care across settings, especially on care transitions from hospitals to post-acute care facilities (Naylor et al., 1999). Work on continuity of care within a setting has focused almost exclusively on patient handoffs in shift-based environments, which are shown to be associated with low quality of care marked by slowdown in service delivery, medical and surgical errors, malpractice cases with communication problems, and (potentially preventable) adverse patient outcomes (Laine et al., 1993; Petersen et al., 1994; Riesenberg et al., 2009). However, the external validity of results in a shift-based environment may be weak when considering non-shift based environments, such as home health. Shift-based handoffs are inevitable due to a trade-off between the length of a shift and the number of handoffs. When physician or nurse shifts are lengthened, a patient is more likely to see the same provider during the course of treatment. At the same time, a longer shift would increase provider fatigue and the risk of making mistakes, especially, towards the end of long shifts (Brachet et al., 2012). In contrast, in home health care, handoffs are largely avoidable through coordinated scheduling given that providers typically visit patients with several days in between. In our data, 38% of patients are seen consistently by a single nurse throughout their episode of care. Hence, zero handoffs are frequent in a non-shift based environment. At the same time, prioritizing continuity of care may be costly in that it may come at the expense of flexibility in scheduling, employee satisfaction, and ultimately retention.

Quantifying the effect of discontinuous home health care has important implications for the use of workforce assignment in improving quality of care, and provides a currency to assess the importance of prioritizing care continuity over other goals typically achieved through schedule architecture. Previous literature has focused almost exclusively on shift-based provider handoffs in large healthcare facilities. Moreover, the literature has focused mostly on nurse staffing levels rather than assignment structure among the workforce strategies used by health care delivery organizations (Aiken et al., 2002; Bae et al., 2010; Needleman et al., 2011; Cook et al., 2012; Lin, 2014; Lu and Lu, 2016; Hockenberry and Becker, 2016).

The outline of the article is as follows. In Section 3.2, we describe the data and present our measures of care discontinuity. In Section 3.3, we discuss our identification strategy. In Section 3.4, we discuss our baseline empirical results as well as our IV estimation results. In Section 3.4.3, we explore the sequencing of handoffs in explaining the relationships between handoffs and the rehospitalization outcome. Section 3.5 concludes the chapter.

3.2. Data

3.2.1. Data and Summary Statistics

This chapter uses a novel and rich data set of home health visits, patient health status assessment, and provider work logs as well as indicators for patient hospital readmissions. We obtained data on all home health stays for Medicare patients from a large for-profit freestanding home health company, which provides home health care services in 89 offices in 16 states.[8][9] Since each office autonomously decides scheduling and staffing and is run as a profit center, we can regard each office as a separate hiring and contracting unit in our empirical analysis. This large set of independently run offices alleviates some concern about the generalizability of our results to other HHAs even if they all belong to one company.[10]

[8] These offices are located in 16 states: Arizona, Colorado, Connecticut, Delaware, Florida, Hawaii, Massachusetts, Maryland, North Carolina, New Jersey, New Mexico, Oklahoma, Pennsylvania, Rhode Island, Virginia, Vermont.

[9] David et al. (2013) show that in vertically integrated HHAs owned by hospitals, post-acute care patients are admitted to HHAs in earlier stages of recovery without a significant difference in readmission rates.

[10] During 2013, compared to a national sample of freestanding agencies, home health offices in our sample tend to be larger, have a lower share of visits provided for skilled nursing and instead have a higher share of visits provided for therapy, and have a lower share of episodes provided to dual-eligible Medicare or Medicaid beneficiaries, which seem to be more common characteristics of proprietary agencies (Cabin et al., 2014; MedPAC, 2016a). However, home health offices in our data provide a similar total number of visits per episode and serve a similar age group on average.

Our sample period covers 44 months between January 2012 and August 2015, for which we have full patient, worker, and office data.

Our main outcome is hospital readmission, which is an important marker of quality and can potentially lead to financial penalties for hospitals. Rehospitalizations among patients receiving home health is common. Our analysis focuses on Medicare patients, who comprise a majority of home health patients and have a high probability of hospital readmissions.[11] Furthermore, our analysis focuses on care discontinuity for skilled nursing because most visits are for skilled nursing care and it provides most medically relevant service that could potentially determine the likelihood of hospitalization (Russell et al., 2011).[12]

Our patient data are provided at the patient visit level as well as the patient episode-admission level.[13] To construct our patient-day level data, we merge the patient episode level data with the visit level data. Home health episodes can end by either a discharge or a hospitalization. The exact dates of these end points for each episode are obtained from the home health admission level OASIS data. These data also provide a rich set of health risk factors.

We also obtained human resources data containing work logs for all providers' visits. We merge the patient-day level data with provider-day level work log data to identify hand-offs and link them with hospital readmissions. Separately, we also use the provider-day level work logs to construct instruments of providers' inactivity statuses, as described in Section 3.3.4.

Finally, we construct office-day level data spanning all 89 offices. This data set tracks ongoing episodes and all nurses in each office providing services on each day. This is then

[11] In the data, on average, 69% of home health episodes in each month are paid for by Medicare (including all Medicare FFS, private Medicare Advantage, and Medicare Part B) either as a primary or secondary payer across 93 offices and months during the sample period. Nationally, Medicare patients had 29% readmission rates among post-hospital home health stays (MedPAC, 2014).

[12] In addition to nurses, there are typically additional providers who visit patients during a home health episode. Those include home health aides, physical therapists, speech-language pathologists, occupational therapists, and medical social services workers.

[13] Medicare FFS pays a prospective payment for each 60-day episode. For patients requiring more care, episodes may be extended by another 60 days during a given home health admission.

merged with the patient-day level data to provide office-level demand and supply conditions.

To construct our final patient-day level sample for analyses, we exclude patients who had multiple subsequent home health episodes as these home health stays may have different patterns of visit schedules and provider handoffs.[14] Since our measure of care discontinuity—handoffs—occur across visits, we exclude episodes consisting of a single visit. Finally, we restrict to home health episodes with a prior hospitalization in the past 14 days.[15] Our final sample includes 43,740 unique home health episodes and 1,031,904 patient days under home health.

Table 14 reports the summary statistics at different levels of aggregation: Panel A at the office-day level; Panel B at the patient-episode level; and Panel C at the patient episode-day level. In our sample, 16.6% of episodes involve a hospital readmission, and most of the readmissions occur within 30 days of hospital discharge.[16] The average home health episode in our sample involved 6 nurse visits over a period of 33 days, with 87% of home health episodes involving between 3 and 12 nurse visits.

Figure 6 presents the number of ongoing episodes and number of readmissions occurring by home health day. It suggests that both the probabilities of being under home health care and readmission decline with home health days. Thus, we control for day of home health fixed effects as well as the number of visits and days since last visit to examine the effect of discontinuous care on the probability of rehospitalization across patients with identical number of visits, spacing of visits, and episode length. We discuss this further in Section 3.3.1.

[14] More precisely, enrolling patients into subsequent episodes has been shown to exhibit a degree of strategic behavior. For example, after the introduction of the home health prospective payment system in 2000, agencies increased the number of episodes per patient (Kim and Norton, 2015).

[15] Home health admissions preceded by a hospital stay account for 35.5% of all Medicare home health admissions in our sample.

[16] Another outcome reported in the OASIS survey is death at home. We do not use it as an outcome because it is rare. Out of more than one million patient-days, death occurs at a rate of 0.18%.

3.2.2. Measuring Care Discontinuity: Provider Handoffs

We focus on the notion of provider handoffs to measure care discontinuity. Many studies on care discontinuity focused on shift-based settings in which there is a salient trade-off between the length of shifts and quality of care (Laine et al., 1993; Petersen et al., 1994; Riesenberg et al., 2009; Brachet et al., 2012). By making the shifts longer, you can provide more continuous care but this comes at the expense of providers' fatigue towards the end of the shifts. In contrast, in home health care settings, handoffs can plausibly be eliminated since 24/7 coverage is rare and visits are typically provided with several days in between. In our sample, the average number of days between visits is 5. Thus, continuous home health care can be naturally conceptualized as seeing the same provider repeatedly, and discontinuous care as a break in it—a provider handoff. Handoffs can also capture a disruption in important aspects of care continuity—uninterrupted service delivery and trusting relationship between service provider and client or caregiver—emphasized by the key stakeholders in the home health industry (Woodward et al., 2004).

For the estimation, we define a "handoff state" as a series of days, beginning on the day a visit by a different skilled nurse occurs and ending on one day before the day that the same skilled nurse visits again (i.e. when continuity of care is restored). Put differently, for each patient i and day t, an indicator of having a nurse handoff equals 1 if i's last nurse is different from the nurse who cared for i in the preceding visit; and 0 otherwise.[17] Under this definition of handoffs, only 38% of patient episodes experience no handoff during the episode of care, with the remaining 62% of patient episodes having at least on handoff.

Figure 7 tracks additional variants of handoffs across the home health episode's length. Figure 7 links home health day with the fraction of patient episodes with at least one, two, three or four handoffs. By the 10th home health day, the fraction of episodes with at last

[17]Under this definition of handoffs, a patient could be in a handoff state even on days she has no nurse visit if those days follow a visit during which an actual handoff occurred. We choose this definition because we view that a patient is "at risk" of being readmitted to a hospital after a handoff occurs. Our results are robust to restricting the sample only to visit days (results are available upon request).

one handoff is 54%, 18% with at least two handoffs, 4% with at least three handoffs, and 1% with at least four handoffs. In comparison, by the 30th home health day, the fraction of episodes with at least one handoff is 64%, 39% with at least two handoffs, 21% with at least three handoffs, and 11% with at least four handoffs. Similarly, Figure 8 shows the fraction of patient-days with nurse handoffs conditional on having a nurse visit. Again, handoffs are substantially more likely to occur early in the home health episode and then sharply decline with more home health days.

3.3. Empirical Strategy

3.3.1. Baseline Specification

We estimate linear probability models with the following specification:

$$Readmit_{ikt} = \alpha + \beta H_{ikt} + \gamma V_{ikt} + \delta_1 X_{ikt} + \delta_2 P_{ik} + \delta_3 W_{kt} + \delta_4 D_t + \theta_k + \epsilon_{ikt} \tag{3.1}$$

where $Readmit_{ikt}$ is an indicator variable for whether patient i served by office k is readmitted to a hospital on day t; H_{ikt} is an indicator variable for handoffs described in Section 3.2.2; V_{ikt} is an indicator variable for having a nurse visit; X_{ikt} is a vector of patient-office-day level variables; P_{ik} is a vector of patient-office-level variables; W_{kt} is a vector of office-day level variables; D_t is a day-level variables; θ_k is office fixed effects.

Whether a patient is readmitted to a hospital may depend on the progression of her severity over the course of home health care, making it important to control for dynamic changes in the patient's daily health status. Beyond an initial assessment in the first visit, home health agencies do not systematically measure and collect data on the patient's health status in subsequent visits. Therefore, we cannot directly control for the dynamic changes in patients' health. However, we use a number of dynamic proxies of patients' real-time health status. First, we control for whether a patient has a nurse visit on a given day, V_{ikt}, as a sicker patient is more likely to have a nurse visit. Second, we control for the number of days since last visit by a nurse in the vector X_{ikt} together with the patient-level mean interval of days between consecutive nurse visits in the vector P_{ik}. The variation in the number of days since last nurse visit holding constant the expected frequency of visits during the episode could capture dynamic shifts in the patient's severity since a nurse's additional visit only after a short period of time may suggest that the patient has gotten sicker on that day. Third, for similar reasons, we include in the vector X_{ikt} of patient-office-day level variables the number of days since last visit by any provider since the greater the gap between any home health visits, the more likely a patient is to have a readmission controlling for the average frequency of nurse visits. Fourth, we control for the cumulative number of nurse visits provided to control for the effect of dynamic care intensity.[18]

In the vector P_{ik} of patient level variables, we also include the following three groups of variables to adjust for underlying health risks of patients. First, a set of indicator variables associated with high risk of hospitalization, including history of 2 or more falls in the past 12 months, 2 or more hospitalizations in the past 6 months, a decline in mental, emotional, or behavioral status in the past 3 months, currently taking 5 or more medications, and others. Second, a set of indicator variables for patient demographics: age dummies for each age 66-94 and age 95 or higher (reference group is age 65), gender, race, insurance type, an indicator for having no informal care assistance available, and an indicator for living alone.[19] Third, a set of indicator variables for comorbidity factors, including indicators for 17 Charlson comorbidity index factors, indicators for overall health status, indicators for high-risk factors including alcohol dependency, drug dependency, smoking, obesity, and indicators for conditions prior to hospital stay within past 14 days including disruptive or socially inappropriate behavior, impaired decision making, indwelling or suprapublic

[18]Additional potentially relevant variables to include in the vector X_{ikt} are the cumulative number of unique nurses the patient has seen by home health day t and the number of times each nurse has seen the patient. These variables capture an aspect of care disruption that is potentially more meaningful for patients experiencing a large number of handoffs. For example, a patient experiencing six handoffs may be cared for by six different nurses, or may experience multiple handoffs between the same two nurses. Our results are robust and even stronger when controlling for these two additional variables (these results are available upon request).

[19]Insurance types include Medicare Advantage (MA) plans with a visit-based reimbursement, MA plans with an episode-based reimbursement, and dual eligible with Medicaid enrollment (reference group is Medicare FFS).

catheter, intractable pain, serious memory loss and/or urinary incontinence.[20]

In the vector W_{kt} of office-day level variables, we include the number of ongoing episodes and the number of skilled nurses working in the office-day to control for the time-variant caseload and labor supply conditions in each office.

The vector D_t includes indicators for each home health day, indicators for each day of week, and indicators for each month-year. The home health day fixed effects absorb any unobserved fixed characteristics of home health care depending on the timing within an episode, as illustrated in Figures 6, 7, and 8. We also control for month-year pairs as well as day of week indicators to control for any time-specific component of the variation in the likelihood of readmission such as lower probability of readmission in months with major holidays or weekends. The office fixed effects θ_k absorb time-invariant office-specific or geographic differences in hospital readmissions, for example, through different hospital policies or state regulations concerning patient readmissions, such as states with Certificate-of-Need (CON) laws imposing home health entry restriction (Polsky et al., 2014). Our estimates of the effects of handoffs would be based on the difference in the readmission rates between patients who experience a nurse handoff and those who do not on the same home health day, same month-year, day of week as well as in the same office after controlling for other observed characteristics discussed above.

3.3.2. Identification Challenges

Indicator variables for experiencing a handoff and having a nurse visit are endogenous due to the non-random provision of continuous care and nurse visits. To provide a plausibly causal estimate of the effect of handoffs on hospital readmissions, we need to use an exogenous measure of handoffs. To understand the identification strategy, rewrite the equation (3.1) in a more general form where the readmission outcome $Readmit_{ikt}$ is a function of handoffs H_{ikt}; an indicator variable for having a nurse visit scheduled V_{ikt}; other observable

[20] Indicators for overall health status include indicators for very bad (patient has serious progressive conditions that could lead to death within a year), bad (patient is likely to remain in fragile health) and temporarily bad (temporary facing high health risks).

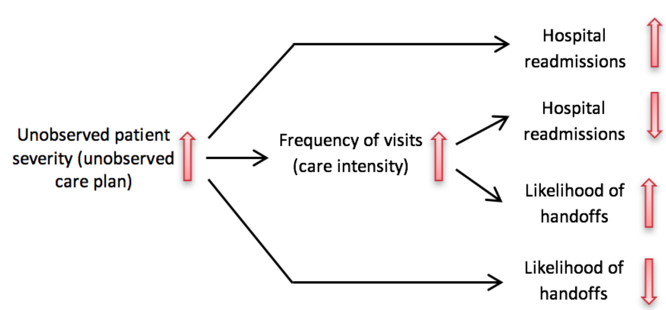
patient characteristics at the patient-office-day level X_{ikt}; observable patient characteristics at the patient-office level P_{ik}; office characteristics at the office-day level W_{kt}; time fixed effects D_t; unobservable patient characteristics on each day U_{ikt};and unobserved idiosyncratic component ϵ_{ikt} uncorrelated with H_{ikt}, V_{ikt}, X_{ikt}, P_{ik}, W_{kt}, D_t or U_{ikt}:

$$Readmit_{ikt} = f(H_{ikt}, V_{ikt}, X_{ikt}, P_{ik}, W_{kt}, D_t, U_{ikt}, \epsilon_{ikt}). \tag{3.2}$$

The identification assumption is that the likelihood of handoff varies only with observable patient characteristics and office- or provider-side daily characteristics, and is uncorrelated with unobservable patients' daily severity, i.e.

$$[H_{ikt}, V_{ikt} | X_{ikt}, P_{ik}, W_{kt}, D_t] \perp U_{ikt}.$$

Even though we control for a large number of patient, nurse, office and day characteristics as we described in Section 3.3.1, we lack clear documentation of the care plan for each patient-episode of care. Consequently, we use an indicator variable for actual nurse visits, $\hat{V}_{ikt}$, as opposed to planned ones, V_{ikt}. However, whether a visit is actually provided is plausibly linked with unobserved patient severity and hence with the risk of hospital readmissions, thus resulting in $[H_{ikt}, \hat{V}_{ikt} | X_{ikt}, P_{ik}, W_{kt}, D_t] \not\perp U_{ikt}$.



Put differently, it is difficult to determine the sign of the bias that omitting important patient characteristics will produce in the link between handoffs and hospital readmissions. The reason is that unobserved severity is potentially linked with handoffs and readmissions both directly and indirectly through care intensity. The direct link suggests that sicker patients are both more likely to experience adverse outcomes leading to hospital readmissions and less likely to experience handoffs since offices may try to provide more continuous care. The indirect link is mediated by care intensity, that is, sicker patients will receive more frequent visits during their episode of care. Higher care intensity lowers the risk of hospital readmission but raises the likelihood of scheduling conflicts leading to handoffs. While the direct link suggests fewer handoffs and higher likelihood of hospital readmissions, the indirect link suggests the exact opposite.

3.3.3. Identification Strategies

As a first step to alleviate some of these concerns, we control for a rich set of patient-day variables that serve as a proxy for dynamic changes in unobserved patient-day level severity, as we explain in Section 3.3.1. These variables include the indicator for having a nurse visit and the number of days since last visit by a nurse or any other provider holding constant the mean frequency of nurse visits. To further address the potential threat of endogeneity, we use detailed provider-day level data on breaks in nurses' availability to instrument for both handoffs and the probability of receiving a visit. The likelihood of having a nurse visit is also endogenous as only the actual visits provided are observed and whether a patient receives a nurse visit is correlated with unobservable daily severity level. The instrument exploits the fact that skilled nurses' absences for various periods of time and reasons affect hospital readmission only through their effects on care discontinuity, that is either through missed visits or handoffs.

Call the vector of nurse availability breaks measures B_{ikt}. Suppose that assumptions hold that (1) B_{ikt} is strongly correlated with the endogenous variables H_{ikt} and $\hat{V}_{ikt}$; (2) B_{ikt} is orthogonal to U_{ikt} conditional on other vectors; and (3) the observable vectors are separable from the last two unobserved vectors in $f(\cdot)$ in equation (3.2). We can identify the causal effect of provider handoffs on the likelihood of readmissions by estimating the system of equation (3.2) and

$$H_{ikt} = g(B_{ikt}, X_{ikt}, P_{ik}, W_{kt}, D_t, U_{ikt}, \eta_{ikt}) \tag{3.3}$$

$$\hat{V}_{ikt} = h(B_{ikt}, X_{ikt}, P_{ik}, W_{kt}, D_t, U_{ikt}, \nu_{ikt}) \tag{3.4}$$

using the generalized method of moments, with the instrument moment condition

$$\mathbb{E}\Bigg[\Big\{Readmit_{ikt} - f(H_{ikt}, \hat{V}_{ikt}, X_{ikt}, P_{ik}, W_{kt}, D_t)\Big\}B_{ikt}\Bigg] = 0 \tag{3.5}$$

where η_{ikt} and ν_{ikt} in equations (3.3) and (3.4), respectively, are idiosyncratic error terms for H_{ikt} and $\hat{V}_{ikt}$ uncorrelated with ϵ_{ikt} and U_{ikt}.

3.3.4. Breaks in Provider Availability

For the instrument set B_{ikt} we use breaks in nurse availability on each day as a source of exogenous variation in the likelihood of having a nurse handoff and having a nurse visit. By merging the provider-day level data with the patient-day level data, we track whether the nurse seen by patient i in the last visit is unavailable to serve i today. The last nurse can be assigned to one of six mutually exclusive states in each office k on each day t: (1) Active—visiting patients in i's home office k; (2) Short absence—not providing visits in any office for 1 to 6 consecutive days; (3) Medium absence—not providing visits in any office for 7 to 14 consecutive days; (4) Long absence—not providing visits in any office for 15 to 90 consecutive days; (5) Assigned to other office—providing visits exclusively in a different office; and (6) Attrition—not providing visits in any office for 91 or more consecutive days, or having the employment contract terminated (due to either quit or layoff) according to HR records.[21][22] The instrument vector B_{ikt} includes the above absence indicator variables (2)-(6) with "Active" the omitted category.

[21] We made a judicious choice of this definition of medium absence. We run a robustness check on our main results using an alternative definition of medium absence–not providing visits in any office for 6 to 20 consecutive days–and find very similar results in Table 25 in Appendix 3.6.4.

[22] Since home health visits entail mobility as a nature of work, a provider is not constrained to work for only one office and can visit patients in different offices.

For the validity of the instrument set B_{ikt}, we require that $Corr(B_{ikt}, [H_{ikt}, \hat{V}_{ikt}]') \neq 0$ and $B_{ikt} \perp U_{ikt}$. For the former, it is intuitive that handoffs and missing a visit will be more likely to occur on day t if the nurse who visited the patient in the last visit is unavailable to visit her again on that day. Table 16 presents the distribution of the number of patient episode-day observations as well as the likelihood of having a nurse handoff, a nurse visit, and a hospital readmission for each availability category.[23] In 65% of patient-day observations, the last nurse who visited a patient is available for the same office. As expected, the probability of handoff is lowest at 21% in this subsample compared to all other states corresponding to providers' unavailability. Handoffs occur in 60-70% of patient-day observations in which the nurse who visited the patient in a preceding visit is either on medium or long absence. Similarly, when the last nurse who visited the patient in a preceding visit is unavailable, the patient is less likely to have a nurse visit. The probability of having a nurse visit is approximately 10% or smaller when the last nurse is unavailable while the same probability is 27% when the last nurse is around working at the same office. This comparison suggests a strong correlation between nurses' unavailability and handoffs. Consistent with this, we find first-stage results to be quite strong, as shown later in Table 18.

As for the exclusion restriction, we rely on the notion that nurse inactivity is uncorrelated with unobserved daily patient health conditions or any other unobserved nurse-day level or office-day level characteristics. Such correlation would imply that absence by nurses is linked with their patients' likelihood of readmission. To assess these possibilities, we discuss several ways in which the exclusion restriction condition could be violated and show evidence alleviating those concerns.

First, a potential concern may be that nurses are more likely to become inactive when their patients' health changes. In particular, nurses with patients who are getting progressively sicker may experience burnout and desire a day off. To assess such potential scenarios, Figure 9 plots three key measures of patients' severity by number of days prior to nurse

[23] We provide the same table using an alternative definition of absence categories in Table 24 in Appendix 3.6.4.

inactivity for the stock of patients under the nurse's supervision. These measures are Charlson comorbidity index, overall status likely to remain fragile, and taking 5 or more medications, as reported in the initial OASIS assessment conducted for each patient.[24] For this exercise, we define each nurse's set of patients on each day as those who are currently or last visited by the nurse and who are not handed off to another nurse, rehospitalized, or discharged on that day. We separately report these measures against the number of days prior to inactivity by whether the inactivity is short absence (i.e. not providing any visits for 1-2 consecutive days), medium absence (i.e. not providing any visits for 3-14 consecutive days), and long absence/attrition (i.e. not providing any visits for 15 or more consecutive days or exiting the workforce). The variation in severity measures is driven by compositional changes in types of patients under a nurse's care. Figure 9 shows that there is little variation in patients' severity leading up to nurse inactivity, and if anything, most plots show a slight decline in measures in the day or two leading to absence, suggesting that nurses are more likely to take days off when their patient base is stable. Furthermore, these trends indicate that as nurses approach a period of inactivity, they do not selectively discharge healthier patients and subsequently raise the severity mix of the remaining patients under their care.

Second, there is a concern than nurses' burnout from working extended hours and seeing many patients per day may induce them to become inactive, and at the same time, fatigue and burnout may adversely affect patient outcomes (Aiken et al., 2002). Figure 10 plots the number of patient visits per day as a function of days prior to inactivity. We find that nurses' workload consistently declines before a period of inactivity, with 6 to 7 patient visits per day more than a week prior to inactivity and less than 3 patient visits per day in the three days leading to absence.

Finally, nurses might be more likely to be absent during high-workload days while high workload, combined with more absences, could result in higher readmissions if quality of care was deteriorated. For example, Green et al. (2013) found that hospital nurses antic-

[24] We find these measures to be top predictors of rehospitalization. We report the correlations between each of these variables and the indicator for rehospitalization in Table 23 in Appendix 3.6.3.

ipated high-workload days and strategically elected to take time off from work on those days.[25] However, we find no evidence of increases in office-level daily caseload, arrival of new patients, or number of nurse visits immediately following the onset of absence. Figure 11 plots three office-day level measures: the total number of active patients (i.e. the stock of ongoing episodes), the number of new (admitted) patients, and the total number of nurse visits. These measures are plotted in the 10 days leading to a nurse absence and the 10 days following the onset of a nurse absence. We find no evidence of an increase in the office stock of episodes prior to absence.

Not surprisingly, absence reduces offices' capacity for taking on new cases by about 30% in the first two days following the onset of absence, although by the third day office are back to pre-absence levels. Similarly, the total number of nurse visits falls following absence. These findings strengthen the case for our instrument. Absence does not affect the stock of episodes, but reduces the number of visits, hence fewer patients are visited due to absence and those who are visited are likely to experience a handoff. Contrary to Green et al. (2013) we find that nurses are inactive when office-level workload is stable, number of daily visits is lower and fewer patients discharged from hospitals are seen for the first time by the office. In summary, we expect nurse absence in a given day to be positively correlated with the likelihood of handoffs and negatively correlated with the likelihood of visits, but presumably uncorrelated with other factors influencing the likelihood of hospital readmissions. To the extent that different lengths and types of absence provide an exogenous source of variation in the likelihood of handoffs, changes in hospital readmissions should not be driven by nurse absences.

[25]Workload in a hospital is likely unrelated to nurse staffing, that is, patients are not turned down by hospitals due to temporary fluctuation in nurse staffing. On the other hand, absence in home health is likely to affect the agency's ability to take on new patients and meet the care plan for existing patients. This suggests that the anticipated caseload may be systematically higher than the realized one.

3.4. Results on the Effects of Handoffs on the Likelihood of Rehospitalization

3.4.1. Baseline Results from the Cross-Sectional Estimation

Table 17 shows the baseline coefficient estimates on the handoff state indicator from our cross-sectional analysis using four specifications representing different degrees of model saturation, incrementally introducing additional patient level controls. In all columns, we control for the indicator for having a nurse visit V_{ikt} and variables in the patient-day level vector X_{ikt}, office-day level vector W_{kt}, day level time fixed effects vector D_t, and office fixed effects θ_k, as described in Section 3.3.1. In Columns (2)-(4), we incrementally control for the hospitalization risk, demographic, and comorbidity factors, respectively, whose detailed description is provided above. In all these columns, the reference category is the case of experiencing no handoffs. All reported standard errors allow for arbitrary correlation among patient-day observations within the same office.

We find that within home health day, patients experiencing nurse handoffs are 0.17 percentage points or 24% more likely to have hospital readmissions in all specifications. When restricting to 30-day rehospitalizations, the basis for hospital readmission penalties, the effects of nurse handoffs are slightly lower at 21% increase (see Appendix 3.6.1). For robustness, we also estimate the effects using a fixed effect conditional logit estimation to account for the binary nature of our dependent variable. These results are reported in Appendix 3.6.2.

3.4.2. Results from the Instrumental Variables (IV) estimation

Table 18 reports IV estimation results from using the vector of instruments we discuss in Section 3.3.4.[26] We estimate a two-stage least square (2SLS) using a two-step efficient generalized method of moments (GMM) estimator. Panels A and B report the first-stage results for the indicator variables for having a nurse handoff and for a nurse visit, re-

[26]Table 25 in Appendix 3.6.4 shows the IV estimation results using an alternative definition of medium absence, as explained in Section 3.3.4.

spectively. We find the vector of instrumental variables to be a strong predictor of both endogenous variables regardless of specification. The first-stage F-statistic values are large (above 537 for handoffs and above 213 for visits). In Panel A, not surprisingly, each one of the instruments has a statistically significant positive association with handoffs, with longer absence periods (medium, long and permanent absence) resulting in a greater likelihood of handoffs. Similarly, in Panel B, each instrumental variable is negatively associated with the probability of the patient receiving a nurse visit, although the difference in the magnitude of the coefficient estimates is smaller. Panel C reports the second-stage results regressing hospital readmission per-patient-episode-day on the predicted likelihood of handoff and the predicted likelihood of a visit. We find handoffs to raise hospital readmissions, with a statistically significantly coefficient of that is more than twice in magnitude compared to our cross-sectional findings–54% versus 24%. There is no statistically significant residual effect of having a skilled nursing visit on the probability of hospital readmission. Panel C reports the p-values for the Sargan-Hansen J-statistic values of 0.4-0.5, which suggests that we cannot reject the null hypothesis that the instrument set is exogenous.

3.4.3. Decomposition of the Effect of Handoffs

To explore a potential mechanism behind the overall effect of handoffs on the likelihood of hospital readmissions we find in Section 3.4, we decompose the effect by the frequency and sequencing of handoffs. Patients who experience more handoffs within the same time window may be more likely to become at risk of rehospitalization because the potential harm from provider switches is magnified. Nevertheless, the sequence of handoffs may matter. For example, the first handoff may have a weak effect on rehospitalization but when a critical mass of handoffs takes place, the patient's risk of rehospitalization could increase, suggesting a convex relationship between the handoff number and readmissions. Conversely, it may be the case that the first handoff is the most important one, suggesting a concave relationship between the handoff number and the risk of readmissions. This could happen, for example, if offices are more likely to provide discontinuous care to relatively healthier patients.

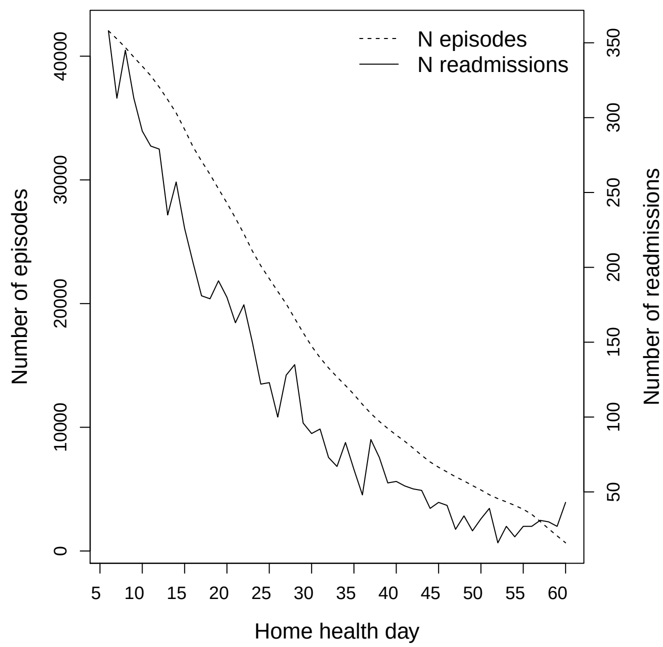
In Table 19, we report the coefficient estimates of interaction terms between the handoff indicator and four frequency indicators for the first, second, third, or fourth and beyond handoffs. Since we include home health day fixed-effects, we are separately comparing patients who experienced their first, second, third or fourth handoff states to those who were not in a handoff state (omitted category) on the same home health day. We find that experiencing one to three handoffs all have a statistically significant effect on the likelihood of readmission. The first handoff is associated with a 35% increase in hospital readmission, the second handoff a 18% increase and the third a 16% increase. The effect of experiencing a fourth handoff and beyond is not statistically significantly different from patients experiencing no handoffs. These results suggest a concave relationship between the frequency of handoffs and the likelihood of readmission, with a decreasing adverse marginal effect of handoffs. It appears that healthier patients tend to get less continuous care and experience more handoffs. Note that this finding is not mechanically driven by sicker patients receiving more visits and having more handoff chances on the same home health day since we control for the cumulative number of nurse visits on each day.

3.5. Conclusion

Greater continuity and coordination of care are an important mechanism in preventing hospital readmissions (Naylor et al., 1999), and post-acute care providers can achieve it through workforce assignment strategies prioritizing care continuity. However, there is little research on the role of workforce assignment affecting care continuity post-discharge. This chapter takes a first step in filling this gap by examining the plausibly causal effect of discontinuity of post-acute care caused by provider switches on hospital readmissions using a novel data set from a large multi-state freestanding home health agency.

Our findings highlight the importance of care continuity prioritization through worker assignment in improving a key competitive performance metric desirable to many health care systems—reduction in hospital readmissions. Studying the elderly Medicare population, we find handoffs to increase hospital readmissions by 54% when instrumenting for handoffs using breaks in availability of previously assigned nurses. A calibration exercise suggests that one in four hospital readmissions during a home health episode would be avoided if nurse handoffs were completely eliminated. Furthermore, we find that patients experiencing handoffs for the first time are more likely to have a hospital readmission relative to those experiencing such handoffs for the second and third time. Our results suggest that preventing handoffs altogether would be an effective way to reduce the likelihood of hospital readmissions. These findings have important implications for scheduling strategies, contracting priorities and regulatory oversight.

Figure 6: The Number of Ongoing Episodes and Readmissions by Home Health Day



Notes: Most first skilled nurse visits and rarely second skilled nurse visits occur within the first 5 days, leading to most patients experiencing no handoffs and dropping out from the sample in this region. Thus, we exclude the first five days of home health care in this plot.

Figure 7: Fraction of Patient Episodes with at Least One, Two, Three, or Four Handoffs by Home Health Day

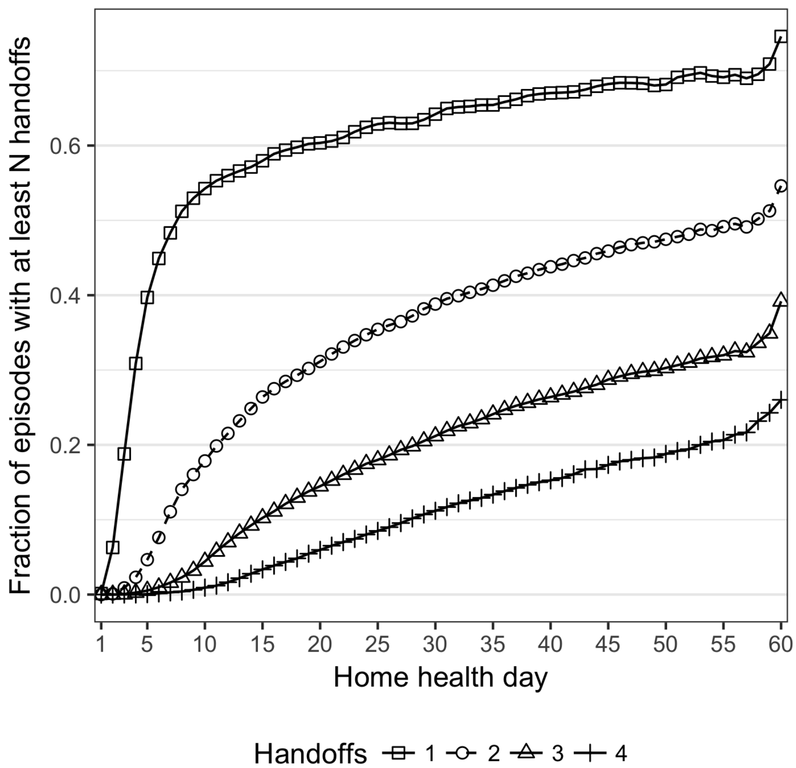
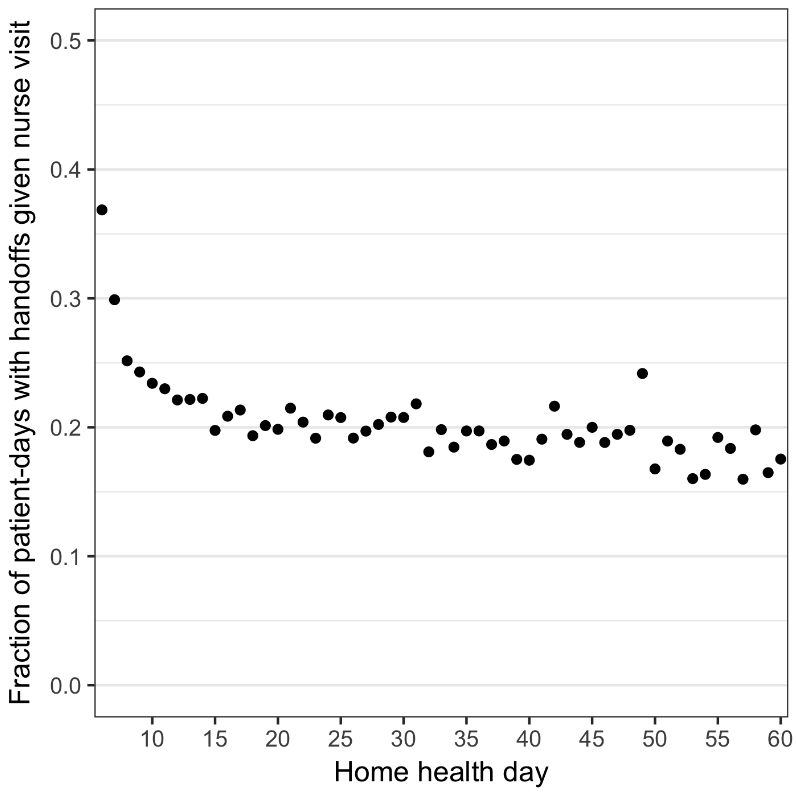


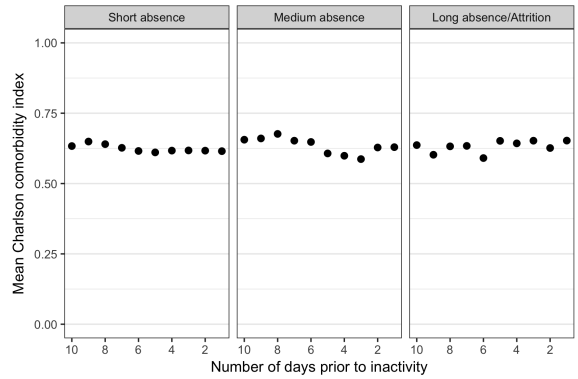
Figure 8: Fraction of Patient-Days with Nurse Handoffs Conditional on Having a Nurse Visit



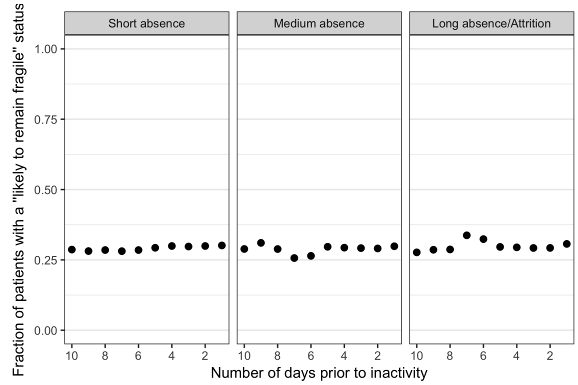
Notes: Most first skilled nurse visits and rarely second skilled nurse visits occur within the first 5 days, leading to most patients experiencing no handoffs and dropping out from the sample in this region. Thus, we exclude the first five days of home health care in this plot.

Figure 9: Measures of Patient Severity Preceding the Nurse's Inactivity

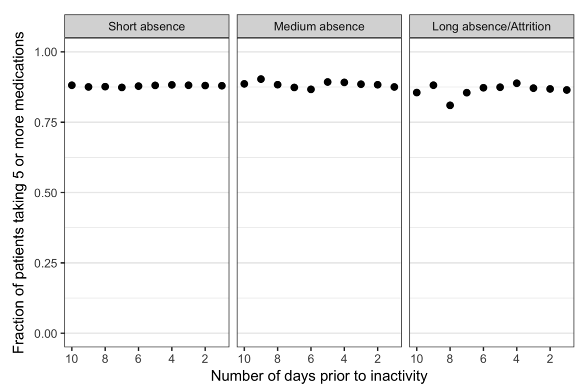
(a) Charlson comorbidity score



(b) Overall status

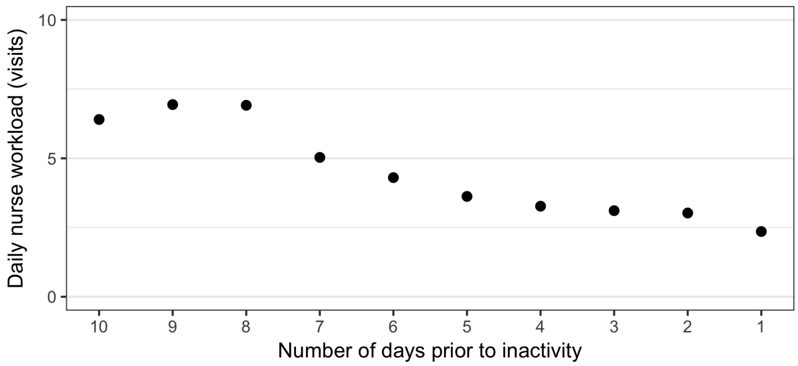


(c) Taking multiple medications



Notes: Mean values are plotted. The inactivity categories are defined as follows: (1) Short absence—not providing visits in any office for 1 to 2 consecutive days; (2) Medium absence—not providing visits in any office for 3 to 14 consecutive days; (3) Long absence/Attrition—not providing visits in any office for 15 or more consecutive days, or not providing visits in any office for 91 or more consecutive days or exiting the workforce (due to either quit or layoff) according to HR records. The sample used for this figure includes all patients who receive home health care.

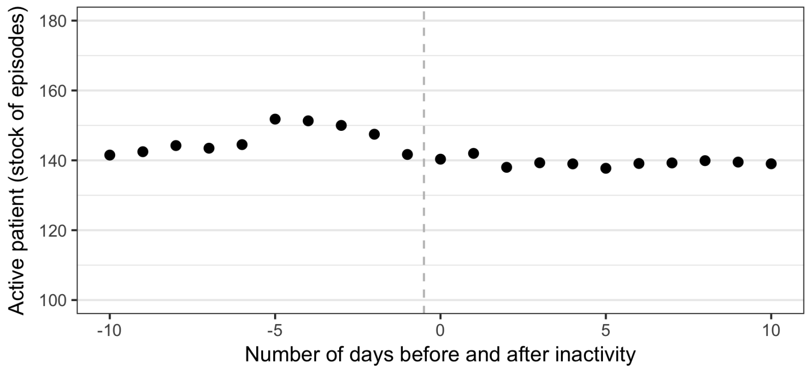
Figure 10: Daily Workload of Nurses Preceding the Nurse's Inactivity



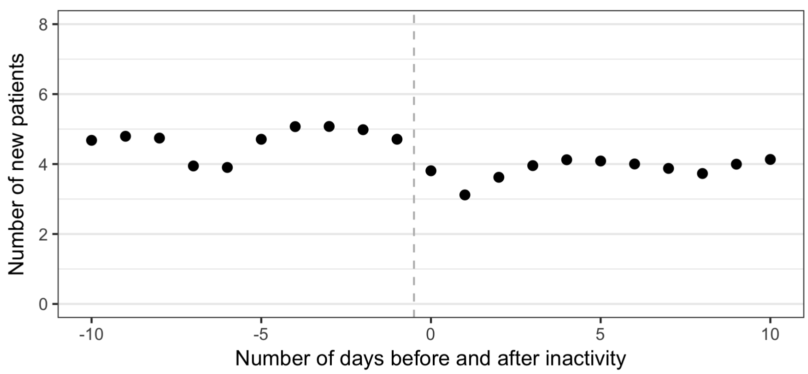
Notes: Mean values are plotted. The inactivity refers to any lengths of absence (i.e. not providing visits temporarily) and attrition (i.e. not providing visits permanently). The sample used for this figure includes all patients who receive home health care.

Figure 11: Daily Office Caseload Before and After the Nurse's Inactivity

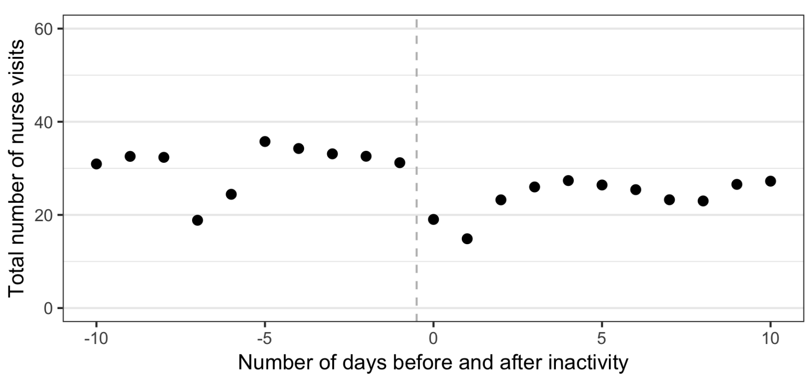
(a) Daily number of ongoing episodes



(b) Daily number of new episodes



(c) Daily number of nurse visits



Notes: Mean values are plotted. The inactivity refers to any lengths of absence (i.e. not providing visits temporarily). The sample used for this figure includes all patients who receive home health care.

Table 14: Sample Summary Statistics for the Sample Period 2012–2015

Variables	Mean	Std Dev
A. Office-day-level variables (Number of observations = 92,676)		
Number of ongoing episodes	113.098	68.345
Number of active nurses	14.596	10.908
B. Patient episode-level variables (Number of observations = 43,740)		
Hospital readmission	0.166	0.372
Hospital readmission within 30 days of hospital discharge	0.130	0.337
Death	0.003	0.053
Length of episode (in days)	32.672	16.268
Number of nurse visits	5.791	3.067
Number of nurse handoffs	1.327	1.600
Mean number of days between nurse visits	5.251	2.948
Age	78.961	8.423
Female	0.598	0.490
White	0.820	0.384
Living alone	0.234	0.423
No assistance available	0.017	0.131
Enrolled in per-visit paying Medicare Advantage	0.190	0.393
Enrolled in per-episode paying Medicare Advantage	0.062	0.242
Dual eligible	0.006	0.078
Risk for hospitalization: History of 2+ falls	0.255	0.436
Risk for hospitalization: 2+ hospitalizations	0.372	0.483
Risk for hospitalization: Recent decline in Mental	0.068	0.251
Risk for hospitalization: Take 5+ medications	0.872	0.334
Risk for hospitalization: Other	0.091	0.288
Acute myocardial infarction (AMI)	0.022	0.148
Congestive heart failure (CHF)	0.130	0.336
Peripheral vascular disease (PVD)	0.016	0.125
Cerebrovascular disease (CEVD)	0.051	0.220
Dementia	0.007	0.084
Chronic pulmonary disease (COPD)	0.104	0.305
Rheumatic disease	0.001	0.030
Peptic ulcer disease	0.003	0.055
Mild liver disease	0.004	0.065
Diabetes	0.017	0.129
Diabetes + Complications	0.009	0.096
Hemiplegia or paraplegia (HP/PAPL)	0.002	0.048
Renal disease	0.029	0.169
Cancer	0.070	0.255
Moderate/severe liver disease	0.002	0.045
Metastatic cancer	0.008	0.089
AIDS/HIV	0.000	0.011
Overall status: (Very bad) Progressive conditions	0.033	0.179
Overall status: (Bad) Remain in fragile health	0.274	0.446
Overall status: Temporarily facing high health risks	0.615	0.487
High risk factor: Alcohol dependency	0.024	0.154
High risk factor: Drug dependency	0.007	0.083
High risk factor: Heavy smoking	0.133	0.340
High risk factor: Obesity	0.163	0.369

Table 14 – *Continued*

	Mean	Std Dev
Pre-HHC condition: Disruptive behavior	0.010	0.102
Pre-HHC condition: Impaired decision-making	0.149	0.356
Pre-HHC condition: Indwelling/Suprapublic catheter	0.018	0.134
Pre-HHC condition: Intractable pain	0.113	0.317
Pre-HHC condition: Memory loss	0.104	0.306
Pre-HHC condition: Urinary incontinence	0.305	0.460
C. Patient episode-day-level variables (Number of observations = 1,031,904)		
Hospital readmission	0.007	0.084
Hospital readmission within 30 days of hospital discharge	0.006	0.074
Handoff	0.265	0.441
First handoff	0.116	0.320
Second handoff	0.073	0.260
Third handoff	0.038	0.190
Fourth+ handoff	0.038	0.192
Handoff from salaried to salaried	0.084	0.278
Handoff from salaried to piece-rate	0.024	0.152
Handoff from piece-rate to piece-rate	0.006	0.074
Handoff from piece-rate to salaried	0.021	0.142
Have a nurse visit	0.203	0.402
Number of days since last nurse visit	4.957	5.232
Number of days since last visit by any provider	2.742	2.771
Cumulative number of nurse visits provided	4.758	2.629
Number of times the current/latest nurse has previously seen the patient	2.544	2.400
Cumulative number of unique nurses the patient has seen	1.863	0.911
Home health day	20.479	12.849

Table 15: Distribution of the Number of Unique Nurses in Each Episode

Number of unique nurses	Number of episodes	Percent
1	16,705	38.19
2	16,918	38.68
3	7,150	16.35
4	2,148	4.91
5	603	1.38
6	155	0.35
7	40	0.09
8	18	0.04
9	3	0.01
	43,740	100.00

Notes. The sample excludes episodes with only 1 nurse visit or more than 20 nurse visits provided, and episodes with more than 15 nurse handoffs.

Table 16: Distribution of Patient-Day Observations and the Likelihood of Nurse Handoff, Nurse Visit, and Readmission by the Availability of Nurse Who Visited a Patient in the Last Visit

	N Obs	% Obs	% Handoff	% Have a nurse visit	% Readmission
Active	670,621	64.99	20.63	27.37	0.77
Short absence (1-6 days)	290,098	28.11	31.07	6.20	0.56
Medium absence (7-14 days)	32,232	3.12	62.45	11.94	0.67
Long absence (15+ days)	13,834	1.34	73.28	11.41	0.71
Assigned to other office	13,415	1.30	49.30	11.20	0.83
Attrition	11,704	1.13	65.02	9.28	0.67
Total	1,031,904	100.00			

Notes. In the entire sample of patient-day observations, the percentage of handoff is 26.46%; the percentage of having a nurse visit is 20.31%; the percentage of readmission is 0.71%.

Table 17: OLS: Patients Experiencing a Handoff Are More Likely to Be Rehospitalized

	Dep Var: Indicator for being rehospitalized			
	(1)	(2)	(3)	(4)
Handoff	0.0017***	0.0017***	0.0017***	0.0017***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
R-squared	0.0067	0.0072	0.0073	0.0081
Observations	1,031,904	1,031,904	1,031,904	1,031,904
Hospitalization risk controls	.	Yes	Yes	Yes
Demographic controls	.	.	Yes	Yes
Comorbidity controls	.	.	.	Yes

Notes. This table presents linear probability models examining whether patients experiencing a handoff are more likely to be rehospitalized. An observation is a patient episode-day. Robust standard errors allowing for arbitrary correlation among episode-days in the same office in parentheses. In all panels and all columns, we control for the indicator for having a nurse visit, cumulative number of nurse visits provided, mean interval of days between two consecutive visits during the episode, number of days since last nurse visit, number of days since last visit by any provider; number of ongoing episodes in the office-day, number of nurses working in the office-day; and office fixed effects, day of week fixed effects, month-year of the day fixed effects, and home health day fixed effects. In columns (2)-(4), hospitalization risk controls include dummies for the risk factors for hospitalization: history of 2+ falls in the past 12 months; 2+ hospitalizations in the past 6 months; decline in mental, emotional, or behavioral status in the past 3 months, currently taking 5+ medications, and others. In columns (3)-(4), demographic controls include age dummies for each age 66-94 and age 95+ (reference group: age=65); female; white; insurance type–Medicare Advantage (MA) plan with a visit-based reimbursement, MA plan with an episode-based reimbursement, dual eligible with Medicaid enrollment (reference group: Medicare FFS); dummy for having no assistance available; dummy for living alone. In column (4), comorbidity controls include dummies for 17 Charlson comorbidity index factors; dummies overall status–very bad (patient has serious progressive conditions that could lead to death within a year), bad (patient is likely to remain in fragile health); and temporarily bad (temporary facing high health risks); dummies for high-risk factors–alcohol dependency, drug dependency, smoking, obesity–and dummies for conditions prior to hospital stay within past 14 days–disruptive or socially inappropriate behavior, impaired decision making, indwelling or suprapublic catheter, intractable pain, serious memory loss, urinary incontinence. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 18: GMM 2SLS: Experiencing Handoffs Increases the Likelihood of Readmission

	(1)	(2)	(3)	(4)
A. First stage - Handoff				
Short absence	0.1327***	0.1327***	0.1326***	0.1326***
	(0.0063)	(0.0063)	(0.0063)	(0.0063)
Medium absence	0.4117***	0.4117***	0.4115***	0.4112***
	(0.0101)	(0.0101)	(0.0101)	(0.0100)
Long absence	0.5301***	0.5303***	0.5298***	0.5294***
	(0.0121)	(0.0121)	(0.0122)	(0.0121)
Other office	0.3003***	0.3003***	0.3001***	0.3001***
	(0.0206)	(0.0206)	(0.0206)	(0.0206)
Attrition	0.4583***	0.4585***	0.4590***	0.4587***
	(0.0156)	(0.0157)	(0.0156)	(0.0157)
R-squared	0.174	0.174	0.174	0.175
F-statistic	538.100	537.186	537.086	540.415
B. First stage - Have a nurse visit				
Short absence	-0.1105***	-0.1106***	-0.1106***	-0.1106***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Medium absence	-0.0956***	-0.0956***	-0.0956***	-0.0956***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Long absence	-0.0934***	-0.0934***	-0.0935***	-0.0934***
	(0.0048)	(0.0049)	(0.0048)	(0.0048)
Other office	-0.1321***	-0.1322***	-0.1320***	-0.1320***
	(0.0071)	(0.0072)	(0.0072)	(0.0072)
Attrition	-0.0784***	-0.0783***	-0.0783***	-0.0778***
	(0.0041)	(0.0041)	(0.0042)	(0.0042)
R-squared	0.244	0.244	0.245	0.245
F-statistic	220.406	218.998	215.463	213.609
C. Second stage - Rehospitalization				
Handoff	0.0036***	0.0037***	0.0039***	0.0038***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Have a nurse visit	0.0036	0.0037	0.0039	0.0039
	(0.0027)	(0.0027)	(0.0027)	(0.0026)
R-squared	0.004	0.005	0.005	0.006
J-statistic p-value	0.503	0.419	0.405	0.437
Observations	1,031,904	1,031,904	1,031,904	1,031,904
Hospitalization risk controls	.	Yes	Yes	Yes
Demographic controls	.	.	Yes	Yes
Comorbidity controls	.	.	.	Yes

Notes. Linear probability models are estimated, using a two-step efficient generalized method of moments (GMM) estimator. Panels A and B show the first-stage results of an IV regression, and Panel C show the second-stage results. We instrument the indicator variables for nurse handoffs and for nurse visits with the following 5 instruments: (1) Active–visiting patients in the patient's home office; (2) Short absence–not providing visits in any office for 1 to 6 consecutive days; (3) Medium absence–not providing visits in any office for 7 to 14 consecutive days; (4) Long absence–not providing visits in any office for 15 or more consecutive days; (5) Assigned to other office–providing visits exclusively in a different office; and (6) Attrition–day post labor termination for nurse according to HR records. An observation is a patient episode-day. Robust standard errors allowing for arbitrary correlation within the same office in parentheses. In all specifications, we control for the cumulative number of nurse visits provided, mean interval of days between two consecutive visits, number of days since last nurse visit, number of days since last visit by any provider; number of ongoing episodes in the office-day, number of nurses working in the office-day; and office fixed effects, day of week fixed effects, month-year of the day fixed effects, and home health day fixed effects. Columns (2)-(4) additionally control for hospitalization risk controls, demographic controls, and comorbidity controls, respectively. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 19: OLS: The Effects of Handoffs Varies by the Frequency and Sequencing of Handoffs

	Dep Var: Indicator for being rehospitalized			
	(1)	(2)	(3)	(4)
First handoff	0.0026***	0.0026***	0.0026***	0.0025***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Second handoff	0.0013***	0.0013***	0.0013***	0.0013***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Third handoff	0.0013***	0.0012***	0.0012***	0.0012***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Fourth+ handoff	0.0008	0.0008	0.0008*	0.0007
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
R-squared	0.0067	0.0072	0.0073	0.0082
Observations	1,031,904	1,031,904	1,031,904	1,031,904
Hospitalization risk controls	.	Yes	Yes	Yes
Demographic controls	.	.	Yes	Yes
Comorbidity controls	.	.	.	Yes

Notes. This table presents linear probability models examining whether the effect on the probability of rehospitalization differs by the frequency and sequencing of handoff. An observation is a patient episode-day. Robust standard errors allowing for arbitrary correlation among episode-days in the same office in parentheses. In all panels and all columns, we control for the indicator for having a nurse visit, cumulative number of nurse visits provided, mean interval of days between two consecutive visits during the episode, number of days since last nurse visit, number of days since last visit by any provider; number of ongoing episodes in the office-day, number of nurses working in the office-day; and office fixed effects, day of week fixed effects, month-year of the day fixed effects, and home health day fixed effects. In columns (2)-(4), hospitalization risk controls include dummies for the risk factors for hospitalization: history of 2+ falls in the past 12 months; 2+ hospitalizations in the past 6 months; decline in mental, emotional, or behavioral status in the past 3 months, currently taking 5+ medications, and others. In columns (3)-(4), demographic controls include age dummies for each age 66-94 and age 95+ (reference group: age=65); female; white; insurance type–Medicare Advantage (MA) plan with a visit-based reimbursement, MA plan with an episode-based reimbursement, dual eligible with Medicaid enrollment (reference group: Medicare FFS); dummy for having no assistance available; dummy for living alone. In column (4), comorbidity controls include dummies for 17 Charlson comorbidity index factors; dummies overall status–very bad (patient has serious progressive conditions that could lead to death within a year), bad (patient is likely to remain in fragile health); and temporarily bad (temporary facing high health risks); dummies for high-risk factors–alcohol dependency, drug dependency, smoking, obesity–and dummies for conditions prior to hospital stay within past 14 days–disruptive or socially inappropriate behavior, impaired decision making, indwelling or suprapubic catheter, intractable pain, serious memory loss, urinary incontinence. *significant at 10%; **significant at 5%; ***significant at 1%.

3.6. Appendix

3.6.1. Analysis Using the 30-Day Readmission Outcome

We report the OLS and 2SLS results estimated using the indicator for rehospitalization within 30 days of hospital discharge in Tables 20 and 21, respectively. We find that the coefficient estimates remain similar, albeit slightly lower in the OLS estimation result and higher in the IV estimation result. The similar size in estimates is not surprising since Table 14 shows that most of the hospital readmission occurs within 30 days of hospital discharge. The IV estimates in Table 21 imply that experiencing a handoff increases the probability of readmission by 0.42–0.47 percentage points (70–78%). The higher percentage changes in this result result from a lower 30-day readmission rate (13%) than the all-time readmission rate (17%).

Table 20: OLS: Patients Experiencing a Handoff Are More Likely to Be Rehospitalized within 30 Days of Hospital Discharge

	Dep Var: Indicator for being rehospitalized			
	(1)	(2)	(3)	(4)
Handoff	0.0015***	0.0015***	0.0015***	0.0015***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
R-squared	0.0074	0.0079	0.0080	0.0088
Observations	1,031,904	1,031,904	1,031,904	1,031,904
Hospitalization risk controls	.	Yes	Yes	Yes
Demographic controls	.	.	Yes	Yes
Comorbidity controls	.	.	.	Yes

Notes. This table presents linear probability models examining whether patients experiencing a handoff are more likely to be rehospitalized within 30 days of hospital discharge. An observation is a patient episode-day. Robust standard errors allowing for arbitrary correlation among episode-days in the same office in parentheses. In all panels and all columns, we control for the indicator for having a nurse visit, cumulative number of nurse visits provided, mean interval of days between two consecutive visits during the episode, number of days since last nurse visit, number of days since last visit by any provider; number of ongoing episodes in the office-day, number of nurses working in the office-day; and office fixed effects, day of week fixed effects, month-year of the day fixed effects, and home health day fixed effects. In columns (2)-(4), hospitalization risk controls include dummies for the risk factors for hospitalization: history of 2+ falls in the past 12 months; 2+ hospitalizations in the past 6 months; decline in mental, emotional, or behavioral status in the past 3 months, currently taking 5+ medications, and others. In columns (3)-(4), demographic controls include age dummies for each age 66-94 and age 95+ (reference group: age=65); female; white; insurance type–Medicare Advantage (MA) plan with a visit-based reimbursement, MA plan with an episode-based reimbursement, dual eligible with Medicaid enrollment (reference group: Medicare FFS); dummy for having no assistance available; dummy for living alone. In column (4), comorbidity controls include dummies for 17 Charlson comorbidity index factors; dummies overall status–very bad (patient has serious progressive conditions that could lead to death within a year), bad (patient is likely to remain in fragile health); and temporarily bad (temporary facing high health risks); dummies for high-risk factors–alcohol dependency, drug dependency, smoking, obesity–and dummies for conditions prior to hospital stay within past 14 days–disruptive or socially inappropriate behavior, impaired decision making, indwelling or suprapublic catheter, intractable pain, serious memory loss, urinary incontinence. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 21: GMM 2SLS: Experiencing Handoffs Increases the Likelihood of Readmission within 30 Days of Hospital Discharge

	(1)	(2)	(3)	(4)
A. First stage - Handoff				
Short absence	0.0879***	0.0879***	0.0879***	0.0880***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Medium absence	0.2707***	0.2707***	0.2706***	0.2706***
	(0.0076)	(0.0076)	(0.0075)	(0.0075)
Long absence	0.3462***	0.3463***	0.3462***	0.3460***
	(0.0104)	(0.0104)	(0.0104)	(0.0104)
Other office	0.2112***	0.2113***	0.2111***	0.2112***
	(0.0143)	(0.0143)	(0.0144)	(0.0143)
Attrition	0.2763***	0.2764***	0.2767***	0.2767***
	(0.0118)	(0.0118)	(0.0118)	(0.0117)
R-squared	0.430	0.430	0.430	0.430
F-statistic	389.119	389.243	393.149	395.680
B. First stage - Have a nurse visit				
Short absence	-0.1115***	-0.1116***	-0.1116***	-0.1116***
	(0.0047)	(0.0047)	(0.0047)	(0.0048)
Medium absence	-0.0981***	-0.0982***	-0.0981***	-0.0982***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Long absence	-0.0972***	-0.0972***	-0.0973***	-0.0973***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Other office	-0.1344***	-0.1345***	-0.1343***	-0.1343***
	(0.0071)	(0.0071)	(0.0071)	(0.0071)
Attrition	-0.0816***	-0.0814***	-0.0815***	-0.0810***
	(0.0041)	(0.0042)	(0.0042)	(0.0042)
R-squared	0.245	0.245	0.245	0.245
F-statistic	222.072	220.780	216.391	214.325
C. Second stage - 30-day rehospitalization				
Handoff	0.0042***	0.0044***	0.0046***	0.0047***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Have a nurse visit	0.0044*	0.0046*	0.0047*	0.0047*
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
R-squared	0.004	0.004	0.004	0.005
J-statistic p-value	0.744	0.669	0.650	0.742
Observations	1,031,904	1,031,904	1,031,904	1,031,904
Hospitalization risk controls	.	Yes	Yes	Yes
Demographic controls	.	.	Yes	Yes
Comorbidity controls	.	.	.	Yes

Notes. Linear probability models are estimated, using a two-step efficient generalized method of moments (GMM) estimator. Panels A and B show the first-stage results of an IV regression, and Panel C show the second-stage results. We instrument the indicator variables for nurse handoffs and for nurse visits with the following 5 instruments: (1) Active–visiting patients in the patient's home office; (2) Short absence–not providing visits in any office for 1 to 6 consecutive days; (3) Medium absence–not providing visits in any office for 7 to 14 consecutive days; (4) Long absence–not providing visits in any office for 15 or more consecutive days; (5) Assigned to other office–providing visits exclusively in a different office; and (6) Attrition–day post labor termination for nurse according to HR records. An observation is a patient episode-day. Robust standard errors allowing for arbitrary correlation within the same office in parentheses. In all specifications, we control for the cumulative number of nurse visits provided, mean interval of days between two consecutive visits, number of days since last nurse visit, number of days since last visit by any provider; number of ongoing episodes in the office-day, number of nurses working in the office-day; and office fixed effects, day of week fixed effects, month-year of the day fixed effects, and home health day fixed effects. Columns (2)-(4) additionally control for hospitalization risk controls, demographic controls, and comorbidity controls, respectively. *significant at 10%; **significant at 5%; ***significant at 1%.

3.6.2. Results from the Conditional Logit Model Estimation

For robustness check, we also estimate a fixed effect conditional logit model to account for the binary nature of our dependent variable. Table 22 reports average marginal effects estimated using the fixed effect conditional logit estimation results. These average marginal effects are even stronger than implied by the OLS and IV estimates.

Table 22: Logit: Patients Experiencing a Handoff Are More Likely to Be Rehospitalized

	Dep Var: Indicator for being rehospitalized			
	(1)	(2)	(3)	(4)
Handoff	0.227***	0.225***	0.226***	0.216***
	(0.0281)	(0.0280)	(0.0279)	(0.0282)
Log likelihood	-35842.873	-35580.826	-35534.201	-35183.389
Observations	1,031,904	1,031,904	1,031,904	1,031,904
Hospitalization risk controls	.	Yes	Yes	Yes
Demographic controls	.	.	Yes	Yes
Comorbidity controls	.	.	.	Yes

Notes. This table presents average marginal effects estimated using the fixed effect conditional logit estimation results. An observation is a patient episode-day. Robust standard errors allowing for arbitrary correlation among episode-days in the same office in parentheses. In all panels and all columns, we control for the indicator for having a nurse visit, cumulative number of nurse visits provided, mean interval of days between two consecutive visits during the episode, number of days since last nurse visit, number of days since last visit by any provider; number of ongoing episodes in the office-day, number of nurses working in the office-day; and office fixed effects, day of week fixed effects, month-year of the day fixed effects, and home health day fixed effects. In columns (2)-(4), hospitalization risk controls include dummies for the risk factors for hospitalization: history of 2+ falls in the past 12 months; 2+ hospitalizations in the past 6 months; decline in mental, emotional, or behavioral status in the past 3 months, currently taking 5+ medications, and others. In columns (3)-(4), demographic controls include age dummies for each age 66-94 and age 95+ (reference group: age=65); female; white; insurance type–Medicare Advantage (MA) plan with a visit-based reimbursement, MA plan with an episode-based reimbursement, dual eligible with Medicaid enrollment (reference group: Medicare FFS); dummy for having no assistance available; dummy for living alone. In column (4), comorbidity controls include dummies for 17 Charlson comorbidity index factors; dummies overall status–very bad (patient has serious progressive conditions that could lead to death within a year), bad (patient is likely to remain in fragile health); and temporarily bad (temporary facing high health risks); dummies for high-risk factors–alcohol dependency, drug dependency, smoking, obesity–and dummies for conditions prior to hospital stay within past 14 days–disruptive or socially inappropriate behavior, impaired decision making, indwelling or suprapublic catheter, intractable pain, serious memory loss, urinary incontinence. *significant at 10%; **significant at 5%; ***significant at 1%.

3.6.3. Correlation of Selected Measures of Patients' Severity and Rehospitalization

Table 23 presents coefficient estimates on three selected measures of patients' severity—indicators for each category of Charlson comorbidity index, overall status likely to remain fragile, and taking 5 or more medications—obtained from estimating the model in Column (4) of Table 17. We find that reported severity measures are statistically significant and strong predictors of the likelihood of readmission, even stronger than handoff.

Table 23: Key Measures of Patients' Severity as Predictors of the Likelihood of Readmission

	Dep Var: Indicator for being rehospitalized
Handoff	0.0017***
	(0.0002)
A. 17 Components of the Charlson Comorbidity Index	
Acute myocardial infarction (AMI)	0.0001
	(0.0007)
Congestive heart failure (CHF)	0.0028***
	(0.0003)
Peripheral vascular disease (PVD)	0.0026***
	(0.0009)
Cerebrovascular disease (CEVD)	0.0008**
	(0.0003)
Dementia	0.0018*
	(0.0011)
Chronic pulmonary disease (COPD)	0.0023***
	(0.0004)
Rheumatic disease	0.0008
	(0.0025)
Peptic ulcer disease	0.0052**
	(0.0020)
Mild liver disease	0.0016
	(0.0016)
Diabetes	0.0014**
	(0.0007)
Diabetes + Complications	0.0057***
	(0.0013)
Hemiplegia or paraplegia (HP/PAPL)	0.0002
	(0.0017)
Renal disease	0.0032***
	(0.0007)
Cancer	0.0041***
	(0.0005)
Moderate/severe liver disease	0.0067***
	(0.0024)
Metastatic cancer	0.0045***
	(0.0015)
AIDS/HIV	0.0107
	(0.0115)
B. Overall Status	
Likely to remain in fragile health	0.0034***
	(0.0004)
C. Risk for Hospitalization	
Take 5 or more medications	0.0005*
	(0.0003)
R-squared	0.0081
Observations	1,031,904

Notes. An observation is a patient episode-day. Robust standard errors allowing for arbitrary correlation among episode-days in the same office in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.

3.6.4. Robustness Check Using an Alternative Definition of Breaks in Nurses' Availability

In this appendix, we run a robustness check on our main IV results using an alternative definition of medium absence. We define medium absence as not providing visits in any office for 6 to 20 consecutive days, and accordingly, short absence for 1 to 5 consecutive days and long absence for 21 or more consecutive days.

Table 24 presents the distribution of the number of patient episode-day observations as well as the likelihood of having a provider handoff, a nurse visit, and a hospital readmission for each newly defined availability category. The distributions of observations and probabilities of handoffs, nurse visits, and readmissions change little when we use a wider window of time for medium absence. A noticeable difference is an increase in the probabilities of handoffs and readmissions when a provider is having a long absence under the new definition. However, qualitatively, the relative orders of these numbers remain the same across the categories. Therefore, we obtain very similar first-stage and second-stage estimates in Table 25 to those in Table 18. In Panels A and B for the first-stage results, each of providers' unavailability status seems to be a stronger predictor of patients' handoffs and a slightly weaker predictor of patients' receiving nurse visits. However, the F-statistic values are still significantly large. In Panel C, in Column (4), we find a tiny decrease in the magnitude of the effect of experiencing a handoff at 0.37 percentage points or 53% on the likelihood of rehospitalization.

Table 24: Distribution of Patient-Day Observations and the Likelihood of Nurse Handoff, Nurse Visit, and Readmission by the Availability of Nurse Who Visited a Patient in the Last Visit

	N Obs	% Obs	% Handoff	% Have a nurse visit	% Readmission
Active	670,621	64.99	20.63	27.37	0.77
Short absence (1-5 days)	280,872	27.22	29.95	5.94	0.55
Medium absence (6-20 days)	47,559	4.61	63.72	12.22	0.70
Long absence (21+ days)	7,733	0.75	77.42	11.95	0.72
Assigned to other office	13,415	1.30	49.30	11.20	0.83
Attrition	11,704	1.13	65.02	9.28	0.67
Total	1,031,904	100.00			

Notes. In the entire sample of patient-day observations, the percentage of handoff is 26.46%; the percentage of having a nurse visit is 20.31%; the percentage of readmission is 0.71%.

Table 25: GMM 2SLS: Experiencing Handoffs Increases the Likelihood of Readmission

	(1)	(2)	(3)	(4)
A. First stage - Handoff				
Short absence	0.1190***	0.1190***	0.1190***	0.1190***
	(0.0061)	(0.0061)	(0.0061)	(0.0060)
Medium absence	0.4232***	0.4232***	0.4231***	0.4227***
	(0.0101)	(0.0101)	(0.0101)	(0.0101)
Long absence	0.5573***	0.5574***	0.5568***	0.5568***
	(0.0190)	(0.0190)	(0.0191)	(0.0190)
Other office	0.2995***	0.2996***	0.2993***	0.2994***
	(0.0206)	(0.0206)	(0.0206)	(0.0206)
Attrition	0.4571***	0.4574***	0.4578***	0.4575***
	(0.0156)	(0.0156)	(0.0156)	(0.0156)
R-squared	0.178	0.178	0.178	0.179
F-statistic	439.211	439.030	440.619	442.788
B. First stage - Have a nurse visit				
Short absence	-0.1111***	-0.1112***	-0.1112***	-0.1112***
	(0.0048)	(0.0048)	(0.0048)	(0.0048)
Medium absence	-0.0956***	-0.0957***	-0.0957***	-0.0957***
	(0.0032)	(0.0032)	(0.0033)	(0.0033)
Long absence	-0.0945***	-0.0945***	-0.0944***	-0.0943***
	(0.0046)	(0.0046)	(0.0046)	(0.0046)
Other office	-0.1321***	-0.1322***	-0.1320***	-0.1320***
	(0.0071)	(0.0072)	(0.0072)	(0.0072)
Attrition	-0.0785***	-0.0783***	-0.0783***	-0.0779***
	(0.0041)	(0.0041)	(0.0042)	(0.0042)
R-squared	0.244	0.244	0.245	0.245
F-statistic	234.768	232.472	230.006	226.544
C. Second stage - Rehospitalization				
Handoff	0.0035***	0.0036***	0.0037***	0.0037***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Have a nurse visit	0.0036	0.0038	0.0039	0.0040
	(0.0025)	(0.0025)	(0.0025)	(0.0024)
R-squared	0.004	0.005	0.005	0.006
J-statistic p-value	0.626	0.571	0.547	0.617
Observations	1,031,904	1,031,904	1,031,904	1,031,904
Hospitalization risk controls	.	Yes	Yes	Yes
Demographic controls	.	.	Yes	Yes
Comorbidity controls	.	.	.	Yes

Notes. This table presents linear probability models examining whether patients experiencing a hand-off are more likely to be rehospitalized, using a two-step efficient generalized method of moments (GMM) estimator. Panels A and B show the first-stage results of an IV regression, and Panel C show the second-stage results. We instrument the indicator variables for skilled nurse handoffs and for having a nurse visit with the following 5 instruments: (1) Active–visiting patients in the patient's home office; (2) Short absence–not providing visits in any office for 1 to 4 consecutive days; (3) Medium absence–not providing visits in any office for 6 to 20 consecutive days; (4) Long absence–not providing visits in any office for 21 or more consecutive days; (5) Assigned to other office–providing visits exclusively in a different office; and (6) Attrition–day post labor termination for nurse (due to either quit or layoff) according to HR records. An observation is a patient episode-day. Robust standard errors allowing for arbitrary correlation among episode-days in the same office in parentheses. In all columns, regressions include mean interval of days between two consecutive visits during the episode, number of days since last nurse visit for the patient, number of days since last visit by any provider for the patient; number of ongoing episodes in the office-day, number of nurses working in the office-day; office fixed effects, day of week fixed effects, month-year of the day fixed effects, home health day fixed effects; and hospitalization risk controls, demographic controls, and comorbidity controls. *significant at 10%; **significant at 5%; ***significant at 1%.

APPENDIX

A.1. Home Health Care Industry

Home health care, which is provided to homebound patients who need skilled nursing or therapy services, is an important and rapidly growing segment of the post-acute care delivery system. The number of home health agencies (HHAs), which are the major providers of home health care, had grown from 9,291 to 12,461 by 34% between 2007 and 2014 while Medicare fee-for-service (FFS) spending on HHAs has increased from $22.8 billion to $29.1 billion by 28% during the same period (MedPAC, 2016b). Moreover, between 2006 and 2014, home health care had the highest growth of 3.1% as a destination for all Medicare fee-for-service (FFS) patients who were discharged from an acute care hospital (MedPAC, 2016b).

This rapid growth may be attributed to its appeal to patients who prefer to recover at home, providers who prefer to shorten hospitalization lengths, and insurers who benefit from cheaper care at home than care in brick-and-mortar institutions. A demographic change from aging population and technological advancement allowing for the care delivery at home—including greater curative capacity of drugs which can be easily administered at home and evolution of medical and telecommunications devices facilitating mobility of care delivery—also contribute to the growth of home health care. Not surprisingly, the number of Medicare FFS home health care users has grown by 36% and FFS spending for home health care has risen by 108% during 2000–2014 (MedPAC, 2016a). The importance of home health care has also increased with the rise of enhanced care coordination and shared savings models such as Accountable Care Organizations or Bundled Payments for Care Improvement as well as financial incentives to prevent hospital readmissions, known as the Hospital Readmissions Reduction Program, under the Affordable Care Act (David and Kim, 2017).

For the source of payment, health insurance, and particularly Medicare, are primary payers for home health care. 88% of the national home health expenditures in freestanding HHAs are paid for by health insurance, 9% by out-of-pocket payments, and 3% by other third-party payers and programs (MedPAC, 2016a).[1] Within health insurance, Medicare is the largest payer, paying for 42% of the national home health care expenditures while Medicaid and private health insurance pay for 36% and 22%, respectively (MedPAC, 2016b). In our data, Medicare is an even more dominant source of payment, accounting for 69% of episodes in each month in my data. Medicare fee-for-service (FFS) makes prospective payment on the basis of a national standardized 60-day episode payment rate that is adjusted for the applicable case-mix and wage indices (Federal Register, 2014). A home health admission can comprise multiple episodes with renewal of another 60-day episode for patients requiring more home health care.[2] Since Medicare FFS is a dominant payer, I measure the quantity of demand provided by firms using the number of 60-day episodes, as I will elaborate in Section 2.4. Moreover, I assume a fixed price in my model in Section 2.3.

A.2. Home Health Care Workforce

There are six home health service disciplines covered by Medicare: skilled nursing (SN), home health aide (HH), physical therapy (PT), speech-language pathology (ST), occupational therapy (OT), and medical social services (MSW). In Table 26, I report the summary statistics of the number of workers firms employ each week for each of these disciplines and two additional disciplines they provide service for, fitness specialists (FS) and registered dietitians (RD). Each week, firms hire 13 skilled nurses—either registered nurses (RNs) or licensed practice nurses (LPNs), though mostly RNs—on average, and for the largest number of weeks compared to other disciplines. Firms hire 11 physical therapists on each week on average and for nearly as many weeks as skilled nurses. The payment rate is increased when the episode involves a higher number of therapy visits, leading to high employment of

[1] HHAs can largely be either freestanding (85% of all HHAs as of 2014) or hospital-based (MedPAC, 2016b).

[2] In comparison, most private Medicare Advantage (MA) plans make payment on the basis of per-visit rate with different cost sharing according to plans. In the data, 25% of MA episodes are paid for on the 60-day episode basis, and 75% on the per-visit basis.

physical therapists in HHAs. However, for other therapy disciplines, such as occupational therapy and speech-language pathology, firms hire 5 and 2 workers per week on average. These smaller numbers reflect lower demand for these services. Firms hire 4 home health aides each week on average but not for as many weeks.

Table 26: Summary Statistics on the Number of Workers in Each Home Health Service Discipline

Discipline	N	Mean	Standard Deviation
Discipline	N	Mean	SD
Skilled nursing (SN)	108,416	12.66	6.19
Physical therapy (PT)	90,820	10.82	4.9
Occupational therapy (OT)	41,046	5.39	2.89
Home health aide (Aide)	24,746	3.66	2.73
Fitness specialist (FS)	411	3.09	1.45
Speech-language pathology (ST)	16,683	2.34	1.34
Medical social services (MSW)	10,728	1.4	0.63
Registered dietitian (RD)	1,451	1.16	0.42

Notes. The unit of observation is a firm-week observation. A single person may be counted multiple times if they have multiple disciplines in the same firm-week. However, these cases are rare, accounting for less than 1% of observations.

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