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ABSTRACT

Home health care has experienced significant growth as an industry and is viewed as one of the avenues for achieving reductions in the cost and utilization of expensive downstream health care services. Using a novel dataset on home health care visits, this study quantifies the effects of reduced time spent with patients during a post-acute home health visit on hospital readmissions. We focus in particular on the subset of patients with conditions that are subject to penalty under the Hospital Readmission Reduction Program. Since both visit length and readmission risk are likely to be correlated with unobserved illness severity, we use the daily sequence of provider visits and deviation from the provider's average daily workload as instruments for visit length. We find that patients who are visited later in the provider's day as well as those who are visited by a provider who has a higher than usual workload experience home health visits that are shorter than usual. Using our instruments and controlling for patient, visit, and provider characteristics, we find that home health visits that are longer than usual by one minute reduce the risk of hospital readmission by approximately 8 percent. These effects seem to be driven by providers with higher levels of discretion in their time management and care provision. We suggest several approaches that managers could take to attain reductions in readmissions without incurring significant additional costs.

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1. Introduction

Home health care is a rapidly growing sector of the health care industry in the United States. Home health care services encompass a broad range of post-acute care services that can be provided at home, including skilled nursing care, physical therapy, and medical social services. These services are intended to provide patients a way to receive care within the comfort of their homes and in a less expensive way, with the goal of ultimately avoiding unnecessary readmissions to the hospital. In light of national conversations around lowering the cost of care and fueled by the belief that greater reliance on home health may help reduce preventable hospital readmissions, the utilization of home health care services has grown significantly in recent years. From 2004 to 2014, the number of home health agencies increased by 63 percent. By 2015, the number of Medicare beneficiaries receiving home health care reached 3.5 million, and Medicare spending for home health services that year was $18.1 billion (MedPAC 2017).

Despite the rapid and significant growth of home health care, there exists limited research regarding its overall effectiveness and, in particular, its effectiveness in preventing expensive hospital readmissions. As hospitals are now subject to penalties for readmissions under the Hospital Readmission Reduction Program (HRRP), they seek to strengthen their monitoring and oversight over their patients post-discharge in the hopes of reducing unnecessary readmissions to the hospital. Home health services are viewed as one such avenue to attain this objective. By potentially identifying health concerns earlier and addressing them in a timely manner, home health providers may effectively preempt the need for a readmission, and thereby allow hospitals to extend the provider-patient interaction period beyond the inpatient stay. If this were the case, it may be welfare-enhancing to make additional capacity investments in home health to ensure sufficient access and availability. On the other hand, it is also possible that home health visits, which represent additional consumption of health care services, do not result in any measurable cost-savings to the overall system. For example, in the case of primary care e-visits, Bavafa et al. (2018) find that the availability of e-visits leads to an *increase* in office visits as opposed to a decrease; in other words, e-visits were being used to complement rather than substitute for traditional office visits. In the case of home health, Polsky et al. (2014) use restriction on competition within markets to show that patients in areas with higher reliance on home health are more likely to be discharged to home health and less likely to experience a hospital readmission. While home health may contribute to reductions in hospitalization, it is unclear what are the mechanisms underlying this phenomena and at what resource cost. It may be that some home health visits add to the overall consumption of health care rather than prevent (and, in effect, substitute) hospital readmissions. Thus, understanding the effects of home health visits on readmission rates is an important empirical question, the answer to which has implications for whether and how to promote these services.

In this study, we use proprietary data from a large multi-state home health agency to address the following question: Does an increase in the relative length of a home health visit lead to a measurable reduction in readmission likelihood? Specifically, what is the nature of this relationship for patients with conditions that would subject the hospital to penalties under HRRP? In our analyses, we focus on the length of a home health visit because this is an operational measure that is directly tied to the effective capacity of the home health provider. Furthermore, we focus on the length of the visit *relative* to the average length of home health visits experienced by a patient during a given episode because patients with different underlying conditions and health care needs are expected to have different baseline visit lengths.

Methodologically, estimating these effects are challenging because of the endogenous nature of the length of a home health visit: Providers are more likely to spend more time (i.e., have longer visits) with sicker patients, and sicker patients are also more likely to be readmitted to the hospital. Although we work with a rich dataset to characterize patients and their home health visits in our cross-sectional estimation, there are likely aspects of a patient's health condition that home health providers would have used to inform their decisions that are not observable to us as researchers. To address these concerns, we use an instrumental variable approach in which we use two instrumental variables: the visit order (i.e., the order of the visit among all visits conducted by a given provider on a given day) and deviation from typical workload (for a given provider on a given day).

Using these instrumental variables and controlling for observable agency, provider, patient, episode, and visit characteristics, we find the following: For patients with conditions that would subject the hospital to readmission penalties under HRRP, an extra minute relative to the average length of a patient's home health visits reduces their readmission likelihood by approximately 8 percent. When we estimate the effect for all patients, not just those with conditions that would result in a penalty under HRRP, the likelihood of readmission decreases by approximately 5 percent given a home health visit that is one minute longer than the average length of visit for that patient. The managerial implications of these findings are clear: There are potentially significant benefits to reorganizing schedules, assigning patients, and investing in more capacity at the home health level in order to lower readmission rates to hospitals.

In this study, we make several contributions to the literature. First, we add to the growing body of work in health care operations by moving beyond acute care settings and delving further into post-acute care settings. Much of the existing literature has focused on acute care settings, such as the emergency department (e.g., Batt and Terwiesch (2016), KC (2014), Saghafian et al. (2012), Song et al. (2015)), critical care units (e.g., Anderson et al. (2012), Chan et al. (2018), Kim et al. (2015)), and the inpatient setting in general (e.g., Freeman et al. (2016), Kuntz et al. (2015), Senot et al. (2016), Song and Huckman (2018)). There is also increased attention to outpatient settings, such as primary care (e.g., Bavafa et al. (2018), Liu et al. (2010)). Work in the post-acute care space has been much more limited to date, with the exception of recent work on nursing homes by Lu (2012) and Lu and Lu (2016). Within the various post-acute care settings (e.g., skilled nursing facilities, rehabilitation hospitals, home health), this paper focuses specifically on the operations of home health care, which is an area of post-acute care that has been underexplored despite its rapid growth. To date, the operations management literature on home health has been primarily focused on nurse scheduling and routing (Begur et al. 1997, Cappanera and Scutellà 2015, Eveborn et al. 2009). A recent paper by Wallin et al. (2015) has employed a case study method to explore the use of telemedicine in home care. We extend this stream of work by using operational data from home health providers to understand how home health care providers may affect hospital readmissions.

Second, through empirical estimation, we quantify the speed-quality tradeoff in a multistage service process. In doing so, we add to the largely theoretical prior literature on speed-quality tradeoffs (e.g., Anand et al. (2011)). Third, we add to the literature on how improved coordination and incentive alignment can help reduce rework. While our setting is one in which there is not an explicit coordination mechanism in place between the home health provider and the hospital, others that are vertically integrated have arguably better aligned incentives to reduce readmission rates. We discuss how such designs may help with efforts to reduce hospital readmissions. Fourth, we contribute to the growing stream of literature on how discretionary workers affect operations, as most home health providers have considerable discretion in carrying out their work. We discuss several managerial implications in which we specify operational levers that can be employed to reduce the likelihood of hospital readmissions.

The remainder of the paper is organized as follows. In section 2, we discuss the related literature to motivate our hypothesized relationship between the relative length of home health visits and readmission likelihood. Section 3 describes our empirical setting and data. We describe a cross-sectional estimation strategy and corresponding results in section 4. In section 5, we detail our instrumental variable estimation approach and corresponding results, including consideration of mechanisms. Section 6 presents several robustness checks. In section 7, we discuss several managerial implications and conclude.

2. Related literature and theoretical motivation

The central problem we address in this paper is a highly generalizable one that extends to various manufacturing and service settings. Broadly, we seek to estimate a response function to quantify the relationship between an input of effort and an output of performance. Specifically, we estimate this response function in a multistage service process in which we have discretionary servers and heterogeneous customers.

There has been a growing body of literature in operations management that explores this relationship between effort and performance, especially in various service settings. Much of this work has been framed as exploring the speed-quality tradeoff, in which we assume that the quality of service is increasing in the amount of time spent with a customer. Analytically, Anand et al. (2011) illustrate that there is an optimal tradeoff to be made between the amount of time servers choose to spend with customers and the quality of service they provide; this is due to the congestion effects and service costs that accompany longer service times. Empirically, there have been efforts to estimate this relationship, although typically as a second-order effect. For example, KC and Terwiesch (2009) examine how higher levels of workload affect service times, and the extent to which this may also have implications for quality as measured by mortality rates. Song et al. (2017) consider how changes to the disclosure of performance feedback affect service times, and whether there are any potential negative effects with regards to service quality. As such, empirically estimating this relationship between service speed and quality has often been a secondary consideration, although one that is important in and of itself.

There are several reasons that could explain why there has been limited work in service operations that seeks to directly estimate the speed-quality tradeoff empirically. One possibility is that the quality of a service is often challenging to define, let alone measure. Even within a single service setting such as health care, there has been little consensus around what constitutes a good measure of quality and how we should prioritize or emphasize various aspects of quality (Song and Veeraraghavan 2018). In addition, measuring quality outcomes may be challenging as they may take a long time to manifest, making the effects of service speed on quality not immediately apparent (Song and Tucker 2016). In addition, many service settings involve team production, where it is difficult to (a) measure time inputs and (b) attribute portions of time to different individuals. Some recent work in health care operations has sought to address some but not all aspects of these challenges, with researchers examining the effects of faster service on readmission rates. KC and Terwiesch (2012) find that earlier discharge of patients with high clinical severity levels from the cardiac intensive care unit (ICU) leads to an increase in readmission rates, thereby eroding cardiac ICU capacity. Similarly, Anderson et al. (2012) find that patients who are discharged when the post-operative unit is congested are more likely to be readmitted with 72 hours. Though these papers move us closer to understanding longer term quality outcomes (i.e., readmission), they do not address the time attribution challenge arising from the team production of health care services.

This is further complicated in multistage processes, such as care along a continuum, when service aspects at one stage of the process may affect service aspects at a subsequent stage. This mismatch between the setting in which decisions are made about speed and the setting in which its quality consequences are manifested introduces a problem of incentive alignment. If a server's incentives are such that the objective is to optimize locally at a single stage with little or no attention paid to global repercussions (e.g., adverse quality effects at a downstream stage), it may be optimal to increase speed regardless of potential downstream quality implications. However, if the objective is to optimize at the system level (i.e., accounting for all stages in the process), it may be prudent to take into consideration the effects of service speed on quality across stages. In other words, it is possible that obtaining the optimal system-level performance may require some of the sub-processes to have worse performance than is locally optimal (Song and Tucker 2016).

A third challenge stems from the endogenous nature of the relationship between service speed and quality, especially in the presence of discretionary servers. When servers have a high level of discretion over the speed and quality of the services they provide and the sequence in which they provide these services, this introduces a significant amount of variability in speed and quality of the services that they provide (Hopp et al. 2007). Because discretionary servers may use information that is unobservable to the researcher to determine how much effort to put into a task, which may in turn have implications for quality, it is often difficult to identify a causal effect of speed on quality given discretionary servers.

In our setting, we are able to address each of these challenges. First, we use a clear measure of quality: hospital readmission. This is a concrete measure that is agreed upon by practitioners as an important quality outcome (Jencks et al. 2009), and one that practitioners themselves can influence through their work. It is also easy to measure, as a readmission is a discrete event that is tracked by hospitals and payers due to the implications for both clinical quality and reimbursements. In our particular setting of home health care, we are also able to address the common challenge regarding team production and time attribution, as each home health visit involves a single service provider (e.g., a nurse) and a single service recipient (i.e., a patient). Conceptually, readmission in these health care settings is closely related to the idea of rework in other operations settings more broadly. In prior work, scholars have examined how the costs of having to address problems via rework compare to costs associated with greater investment in preemptive services (Ittner 1996). Similar to Ittner (1996), we examine the possibility of reducing the costs associated with rework (i.e., readmissions) by increasing investment in preemption (i.e., home health care).

Second, our setting allows us to explore a truly multistage process, in which a service takes place at one stage (i.e., post-acute care activity such as home health visits) while the quality outcome of a potential readmission is manifested at another (i.e., hospital). Because our setting is one of a free-standing home health agency, as opposed to one that is part of a vertically integrated system to which both a home health agency and the admitting hospital belong, we are able to examine a case of non-aligned incentives. This has the benefit of allowing us to circumvent the concerns of cross-stage spillover internalization, which is likely in a vertically integrated system and hinders us from truly understanding the potential speed-quality tradeoff. Nevertheless, even without vertical integration, it may be possible to coordinate across the different stages involved in the process. Prior work on payment contracts and coordination has examined this in detail (e.g., Guajardo et al. (2012), Kouvelis and Lariviere (2000)). We build on this discussion in section 7.

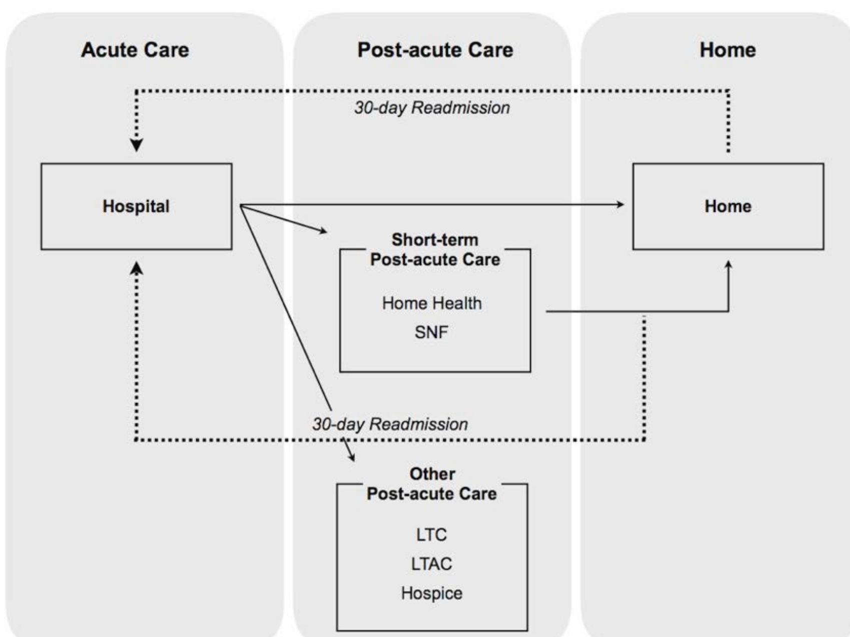
Finally, we are also able to address the endogeneity concerns that arise in trying to causally identify the relationship between service speed and service quality. Endogeneity is primarily an issue because home health providers are discretionary service providers, which means they have significant discretion over how they provide care and how much time they spend doing it. However, in our setting, they exercise little or no discretion over the number of visits that they conduct on a given day and the order in which they conduct these visits. As such, we leverage the exogenous variation in visit order and provider workload as instruments with which to identify the relationship between service speed and service quality. Section 5 describes this methodological approach in greater detail.

3. Empirical setting and data

3.1. Home health care

The focus of this work relates to home health care services and hospital readmissions, which are two elements in a multistage service process. To better contextualize this, first consider the patient flow across the care continuum for a hospitalized patient (Figure 1).

Figure 1 Patient flow across the care continuum



Note. SNF = Skilled nursing facility. LTC = Long-term care. LTAC = Long-term acute care.

After the initial hospitalization (i.e., the acute care encounter), a patient can either (a) be discharged directly to home with no additional care or (b) be discharged to receive some form of post-acute care. Short-term post-acute care could be delivered either at home (via home health) or at another facility (e.g., a skilled nursing facility). Other types of post-acute care include long-term care, long-term acute care, and hospice care. The determination regarding the type of post-acute care that a patient should receive is made by an inpatient physician and is part of the patient discharge plan.

Particularly for patients receiving short-term post-acute care, the goal is for them to eventually be discharged to home, with no additional need for post-acute care or acute care. Part of the reason patients are discharged to short-term post-acute care rather than directly to home is in the hopes of reducing the likelihood of 30-day readmission to the hospital. Of course, this is still a possibility that remains. As such, a patient's trajectory could be either a discharge from short-term post-acute care to home or a hospital readmission during the post-acute care episode.

In this paper, we focus on one form of short-term post-acute care in particular: home health care. Once the determination is made that the patient should receive home health care, the inpatient physician certifies the patient to be eligible for home health care. For the duration of the home health episode, the patient remains under inpatient the physician's care, even if the physician is not the one conducting home visits and directly providing care to the patient. Once initiated, each home health episode begins with a "start of care" visit, during which the provider completes an Outcome and Assessment Information Set (OASIS), which is used to report home health agencies' performance data, and develops a coordinated care plan for the home health episode. Subsequent visits may involve various types of services based on the needs of the patient, including skilled nursing care, physical therapy, occupational therapy, speech-language therapy, and medical social services. Depending on the services needed, each home health visit may involve a different type of provider, including registered nurses, licensed practical nurses, medical social workers, occupational therapists, physical therapists, speech therapists, and home health aides. The home health episode lasts a maximum of 60 days, at which point a patient may either be discharged from home health care or be recertified for another episode of up to 60 days. As described above, a home health episode may also conclude as a result of a hospital readmission.

Care at home by home health agencies, especially following an inpatient hospitalization, is on the rise for many reasons: an aging population, patient preferences for care at home, technological advances that enable treatment and monitoring at the patient's residence, reimbursement pressures, the reduction in informal caregiving due to the growth in labor participation for women, the reduction in number of children per family, and the lower levels of geographical proximity of adults to their elderly parents (David and Polsky 2014). In a post-acute setting, home health care is also associated with earlier discharge, as home health providers can perform some of the recovery services usually administered at the hospital (Gage et al. 2009). In recent years, approximately 14 percent of patients are discharged to home health after an inpatient hospital stay. Medicare beneficiaries who use home health care tend to be older, are more likely to live alone, have multiple chronic conditions, have average daily living activities limitations, and are more likely to live below the federal poverty limit than the average Medicare beneficiary (Avalere 2016). The most prevalent health conditions among home health patients include diabetes, essential hypertension, heart failure, and chronic skin ulcers.

In terms of payment, Medicare reimburses for home health services through a prospective payment system, which includes a base rate that is adjusted annually (Centers for Medicare & Medicaid Services 2018a). This base rate is further adjusted for the severity of a patient's condition and his/her resource use, which is determined using information collected through OASIS. Finally, the base rate is adjusted for the geographic differences in wages, the location type (e.g., payments are increased in rural locations), and any outlier payments incurred during a home health episode.

3.2. Data and sample definition

In this study, we use three years and eight months of proprietary data (January 2012 to August 2015) from a private free-standing for-profit home health agency operating in the United States.[1] This agency has 96 offices in 16 states, where each office makes autonomous staffing and scheduling decisions. For our analyses, we draw on three sources of data: (a) visit-level data, which include detailed information about each home health visit (e.g., date of visit, start time of visit, end time of visit, the visit number within the home health episode, the provider who conducted the visit); (b) episode-level data, which include demographic and risk assessment information collected at the beginning of each home health episode through the OASIS assessment (e.g., age, race/ethnicity, reasons for the prior hospitalization, risk factors, living conditions, health status) and the outcome of the episode (e.g., discharged from home health, recertified, readmitted to the hospital); and (c) human resources data, which include details such as the provider type, contractual status, and daily activities of each provider. We merge these three datasets to create a panel dataset that treats a home health visit as a single observation. We use this full sample to construct several key variables for our analyses, including the visit number within a patient's home health episode, the number of days elapsed between visits within a home health episode, the total number of visits conducted by a provider on a given day, and the order of each visit among all visits conducted by a provider on a given day.

[1] Approximately 85 percent of Medicare-certified home health agencies are free standing, and 70 percent of these agencies are for-profit organizations.

To address our main research question, we then construct an analysis sample by imposing a set of inclusion criteria on the full sample data, some of which we relax in section 6. First, we limit our sample to include only patients who were referred to home health care following discharge from a short-term acute care hospital, which comprises approximately 34 percent of all patients receiving home health care. We impose this restriction because we are specifically interested in exploring hospital readmissions. In effect, this excludes patients who were referred to home health care by outpatient services, skilled nursing facilities, inpatient rehabilitation centers, long-term nursing facilities, and psychiatric hospitals. Second, we limit our sample to exclude readmissions that occurred on the same day as a home health visit (approximately 0.35 percent of the full sample) because it is not possible in these cases to determine the directionality of the relationship between the length of a home health visit and a hospital readmission. For example, after a shorter than usual home health visit, a patient may decide to go to the hospital later that day. Perhaps the provider was running behind or otherwise rushed and missed a problem that could have been addressed in the home health setting. In this case, the shorter than usual visit arguably prompted the readmission. On the other hand, a provider may arrive for a home health visit and cut the visit short due to a determination of the need for inpatient care. This would also manifest in a shorter than usual home health visit. However, in this case, it would be the readmission that prompted the shorter than usual visit length. Third, we exclude days in which a patient received more than one home health care visit (e.g., one visit by a registered nurse and another visit by a physical therapist). This excludes about 29 percent of the full sample. We exclude these because it is unclear to which of the visits one should attribute a subsequent hospital readmission. Fourth, we exclude recertifications (approximately 7 percent of the full sample), which are administratively required visits that document continued patient eligibility for an additional home health episode (up to 60 days). Fifth, we exclude planned hospital readmissions (approximately 5 percent of the full sample), since these are scheduled in advance and are not a function of home health visits. After all of these exclusions, this brings us to 564,878 home health visits comprising 81,473 home health episodes by 2,569 home health providers for 64,620 patients.

For our main analyses, we further restrict our sample to include only those patients with a condition subject to a readmission penalty under the HRRP.[2] These conditions (henceforth, target conditions) include acute myocardial infarction, heart failure, pneumonia, chronic obstructive

[2] Starting in 2012, the Centers for Medicare & Medicaid Services began reducing Medicare payments for hospitals with excess readmissions (after risk adjustment) under the HRRP. According to the Medicare Payment Advisory Commission (MedPAC), 78 percent of hospitals in 2016 had their payment reduced under the HRRP (MedPAC 2017). For more information about HRRP, see `https://www.medicare.gov/hospitalcompare/readmission-reduction-program.html`. For work on the effects of HRRP, see Batt et al. (2018).

pulmonary disease, and hip or knee replacement.[3] This results in an analysis sample that includes 61,344 home health visits comprising 8,867 home health episodes by 1,988 home health providers for 7,482 patients. Note, the number of home health episodes exceeds patients even after excluding recertifications because several patients have had multiple hospitalizations, and a new home health episode is initiated if the subsequent hospitalization did not occur within the maximum episode duration of 60 days.

3.3. Summary statistics

Tables 1a-1c show summary statistics for key visit-, episode-, and provider-level characteristics. In our sample, an average home health visit lasts 47 minutes, and each home health episode is comprised of approximately 14 visits. The large majority of visits are conducted by registered nurses (39%), physical therapists (39%), and occupational therapists (11%). Patients receiving home health care have an average age of 77 and are predominantly white (81%) and female (66%). A significant proportion of these patients are taking 5 or more medications (24%), have a temporarily heightened health status (55%), are living alone (23%), are diabetic (35%), and have mental disorders (38%). On average, a given provider conducts 4.2 home health visits per day.

Table 1a **Visit-level summary statistics (N = 61,344)**

Visit-level variables	Mean	SD
Visit length (minutes)	46.52	18.51
Demeaned visit length (minutes)[a]	0.48	15.66
Number of visits per episode	14.29	9.01
Hospital readmission (%)	2.08	14.27
Visit order (within provider day)	2.62	1.61
Provider type (%)		
Registered nurses	38.58	
Licensed practical nurses	2.94	
Physical therapists	39.17	
Occupational therapists	10.54	
Speech therapists	3.16	
Home health aides	3.91	
Medical social workers	1.55	
Registered dieticians	0.15	

[a] Note, the mean value of the demeaned visit length does not exactly equal zero and its standard deviation does not exactly equal the standard deviation of the (non-demeaned) visit length. This is because the demeaned values are calculated at the episode level rather than by using the entire analysis sample (i.e., without any clustering), whereas the mean and standard deviation of the (non-demeaned) visit length are presented for the entire analysis sample.

[3] Coronary artery bypass graft surgery was added as an additional target condition after our study period.

Table 1b Episode-level summary statistics (N = 8,867)

Episode-level variables	**Mean**	**SD**
Hospital readmission (%)	24.32	42.90
Demographic characteristics		
Age (years)	77.10	12.46
Male (%)	34.30	47.47
Race (%)		
Black	11.59	32.02
White	81.07	39.17
Asian	1.61	12.58
Hispanic	5.47	22.74
Risks for hospitalization		
2+ falls in the past 12 months (%)	19.11	39.32
2+ hospitalization in past 6 months (%)	9.71	29.62
Decline in mental health in past 3 months (%)	3.48	18.34
Currently taking 5+ medications (%)	24.42	42.96
Other risks (%)	10.25	30.33
Health status		
Progressively worse (%)	4.37	20.44
Temporarily heightened (%)	54.82	49.77
Stable (%)	6.36	24.40
Living conditions		
Living alone (%)	23.17	42.19
No assistance available (%)	2.09	14.29
Prior hospitalization reasons		
Disruptive behavior (%)	1.92	14.72
Impaired decision making (%)	18.53	38.85
Indwelling catheter (%)	2.33	15.09
Intractable pain (%)	9.24	28.95
Memory loss (%)	12.87	33.49
Urinary incontinence (%)	37.69	48.46
Unknown (%)	0.91	9.49
None of the above (%)	46.72	49.89
High risk factors		
Alcohol (%)	2.57	15.84
Smoking (%)	22.86	42.00
Drugs (%)	2.19	14.62
Obesity (%)	20.21	40.16
Other health conditions		
Diabetes (%)	34.54	47.55
Mental disorders (%)	37.56	48.43
Other (%)	13.25	33.91

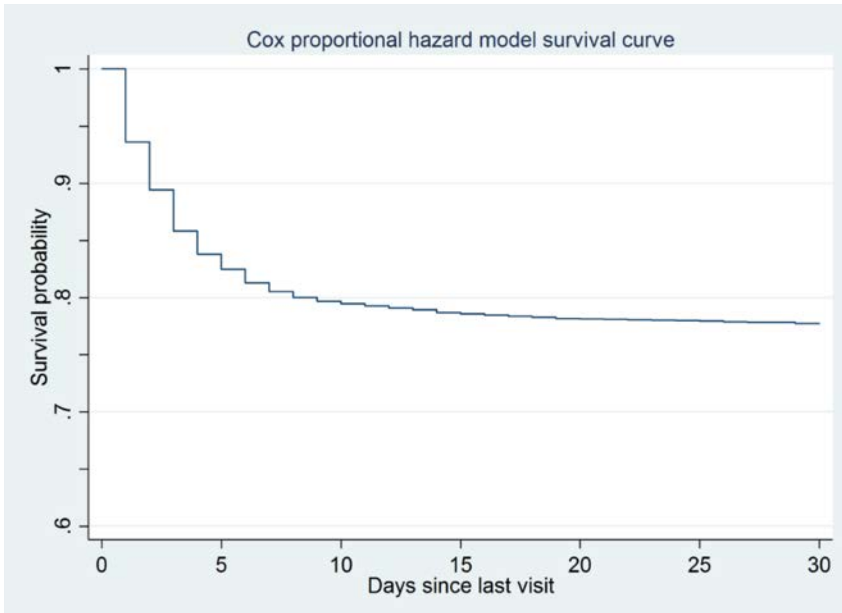
Table 1c Provider-level summary statistics (N = 2,041)

Provider-level variables	**Mean**	**SD**
Workload (daily)	4.20	1.91
Demeaned workload (daily)[a]	0.0006	1.29

[a] Note, the mean value of the demeaned workload does not exactly equal zero and its standard deviation does not exactly equal the standard deviation of the (non-demeaned) workload. This is because the demeaned values are calculated at the provider-month level rather than by using the entire analysis sample for a given provider (i.e., without any month-level clustering), whereas the mean and standard deviation of the (non-demeaned) workload are presented for the entire analysis sample. The demeaned values are calculated at the provider-month level in order to account for the month-to-month variations in a provider's schedule.

On average, 24 percent of home health episodes and 2 percent of home health visits are followed by a hospital readmission. Hospital readmission is an important quality indicator in this setting, especially given our analysis sample is restricted to patients with a target condition.

Figure 2 Survival curve for hospital readmission after the last home health visit



Note. Sample excludes visits that resulted in a same-day readmission. Survival indicates not being readmitted to the hospital.

For patients who do get readmitted to the hospital, the readmission typically happens within one week after the last home health visit. This is captured in Figure 2, which shows the Cox proportional hazard model survival curve for the subset of last visits for all home health episodes in the sample. The survival curve reports the probability of survival (i.e., not being readmitted) at day $1, 2, 3, \cdots, 60$ after the last home health visit.[6] We right-censor all home health episodes at 60 days since the last visit, after which readmission to the hospital becomes difficult to attribute to the home health episode. Figure 2 shows a steep drop in the probability of not being readmitted between days 0 to 6 since the last home health visit, after which the survival curve becomes relatively flat. This suggests that the majority of readmissions happen within one week following a home health visit.

4. Cross-sectional estimation

We use a two-fold empirical approach to explore the effects of the relative length of a home health visit on readmission likelihood: cross-sectional estimation and instrumental variable estimation.

[6] For ease of presentation, we show the survival probability for only the first 30 days after the last home health visit in Figure 2, although we consider up to 60 days after the last home health visit. The survival curve remains relatively flat from days 30 to 60.

4.1. Cross-sectional estimation strategy

First, for the cross-sectional estimation, we estimate a standard linear regression model using an ordinary least squares (OLS) approach. Given the relatively rich set of data concerning patient characteristics and risk factors available, one might expect this approach to provide a reasonably good estimate of the effect. As such, we estimate the following standard linear probability model at the visit level:

$$R_{ijt} = \alpha + \beta \cdot demeaned\_visitlength_{ijt} + \mathbf{X}_i + \theta_t + W_j + \epsilon_{ijt} \tag{1}$$

Here, R_{ijt} is an indicator variable for whether patient visit i conducted by provider j at time t was followed by a readmission to the hospital. The main independent variable of interest is the demeaned length of a home health visit, $demeaned\_visitlength_{ijt}$, which is measured as the deviation of the length of the home health visit i (in minutes) from the patient's average visit length over the course of the home health episode. Specifically, we calculate $demeaned\_visitlength_{ijt}$ by first generating the mean length of all home health visits for a given patient over the course of the home health episode, and then subtracting this mean from the realized length of each home health visit i. As such, a shorter than usual visit would yield a negative demeaned visit length and a longer than usual visit would yield a positive demeaned visit length.

$\mathbf{X}_i$ is a vector of visit- and episode-level characteristics that help us adjust for observable differences in patient characteristics and illness severity. Specifically, we control for prior hospitalization reasons (e.g., impaired decision making, urinary incontinence); high risk factors (e.g., alcohol use, tobacco use, drug use, obesity); living conditions (living alone, no assistance available); risks for hospitalization (history of falls, 2 or more hospitalizations in the last 6 months, decline in mental health in the last 3 months, 5 or more medications being taken); health status (progressively worse, temporarily heightened, stable); and the presence of other health conditions (e.g., diabetes, mental disorders). We also control for various demographic characteristics (age, gender, race/ethnicity) and the start hour of the provider's work day. In addition, we account for the average length of home health visits before visit i, which we refer to as the moving average visit length. This measure tracks the stock of time spent with a patient during a given episode prior to visit i. For example, the moving average visit length at the fourth visit (within an episode) is the average length of home visits summed across visits one, two, three, and four. By construction, the moving average visit length increases when the length of each additional visit gets larger over the course of the episode, and decreases otherwise. We also include a within-episode number-of-visit fixed effect (θ_t) to account for factors associated with the sequential nature of care dynamics (e.g., trends in visit length over the course of a home health episode). By controlling for both the moving average visit length and the visit number fixed effect, we are able to account for differences in the stock of time spent with patients who are at the same stage of their home health episode (i.e., have had the same number of home health visits). This helps us capture relative differences in care intensity across patients at various points of their home health episodes. Finally, we include provider fixed effects (W_j) to account for time-invariant aspects of providers and cluster robust standard errors (ϵ_{ijt}) by home health episode. This allows for the standard errors to be arbitrarily correlated within a given home health episode.

4.2. Cross-sectional estimation results

Table 2 reports the cross-sectional results from estimating equation (1). We present four models in which we sequentially add controls for patient demographics, the start hour of the provider's work day, and the average length of home health visits before visit i. All models include the other control variables described above.

Our main coefficient of interest for the demeaned length of visit is stable across all four specifications. The fully saturated model in column (4) shows that the demeaned length of home health visit is associated with a statistically significant decrease in the likelihood of hospital readmission, although this coefficient is relatively small in magnitude ($\beta = -0.00042$, $p < 0.001$). Nevertheless, given only 2 percent of home health visits are followed by a hospital readmission on average (Table 1a), we can interpret this coefficient to indicate that one extra minute relative to the average length of a patient's home health visit is associated with a 2 percent decrease in the likelihood of hospital readmission.

5. Instrumental variable estimation

Although we include a detailed set of control variables and fixed effects to try to isolate the effect of the demeaned visit length on readmission, we expect there may remain some factors that are not fully accounted for that may be correlated with the demeaned visit length while also affecting the readmission likelihood. In part, this is because the detailed health measures (captured in the OASIS) are collected only at the time of admission to home health and not at each visit. Therefore, the dynamic changes in a patient's health status over the course of a home health episode are not observable to us. As a consequence, the results from the cross-sectional estimation are likely to yield biased estimates due to omitted variable bias, since the error term, ϵ_{ij}, from the OLS specification may be correlated with both R_{ijt} and $demeaned\_visitlength_{ijt}$.

The direction of this potential bias is not *a priori* obvious, as there could be two competing mechanisms. On the one hand, when patients are sicker, they may require more attention from home health providers and thereby receive longer visits while also being more likely to be readmitted to the hospital. On the other hand, during a home health visit, the provider may deem a patient sick

Table 2 Effect of demeaned visit length on readmission (OLS)

	(1)	(2)	(3)	(4)
Demeaned visit length	-0.00031***	-0.00036***	-0.00036***	-0.00042***
	(0.00005)	(0.00005)	(0.00005)	(0.00006)
Hospitalization reasons	Y	Y	Y	Y
High risk factors	Y	Y	Y	Y
Living conditions	Y	Y	Y	Y
Risks for hospitalization	Y	Y	Y	Y
Health status	Y	Y	Y	Y
Other health conditions	Y	Y	Y	Y
Demographic controls		Y	Y	Y
Workday start hour			Y	Y
Moving average visit length				Y
Visit number FE	Y	Y	Y	Y
Provider FE	Y	Y	Y	Y
Observations	61,344	55,172	55,171	55,171
R-squared	0.04216	0.04665	0.04665	0.04681

Notes. Columns (1)-(4) are fixed effects linear probability models estimated at the home health visit level. In all columns, we control for prior hospitalization reasons (dummies for disruptive behavior, impaired decision making, indwelling catheter, intractable pain, memory loss, urinary incontinence, unknown, and none of the above), high risk factors (dummies for alcohol dependency, drug dependency, smoking, and obesity), living conditions (dummies for having no assistance available and for living alone), risk factors for hospitalization (dummies for 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), health status (progressively worse (patient has serious progressive conditions that could lead to death within a year), temporarily heightened (temporarily facing high health risks), stable (patient is likely to remain in fragile health)), and other health conditions (dummies for diabetes, mental disorders, and other), visit number fixed effects, and provider fixed effects. In columns (2)-(4), demographic controls include dummies for age, male, Black, White, Asian, and Hispanic. In columns (3)-(4), we also control for the start hour of the provider's work day. In column (4), we also control for the average visit length of a patient's home health visits before visit i within the same home health episode. Robust standard errors (in parentheses) allow for arbitrary correlation within a given home health episode. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

enough to prompt a readmission, thereby cutting the visit short and resulting in a shorter than usual visit length.

5.1. Instrumental variable estimation strategy

To more directly address these endogeneity concerns arising from unobservable differences in patient severity, we use an instrumental variable approach. This allows us to causally estimate the effect of the relative length of a home health visit on the likelihood of readmission. We use two instruments in our analyses: (a) the order in which a patient was visited by a provider on a given day and (b) deviations from a provider's typical daily workload. Our first instrument, visit order, captures the sequential order that patient visit i happened to occupy among all visits that were conducted by provider j on a particular day. Note, we construct the visit order variable using the full dataset that also includes patients who were referred to home health care by physicians in the community, patients in recertified episodes, and patients without a target condition, so that we accurately capture the order in which a given patient was visited by a given provider on a given day. Our second instrument, provider demeaned workload, captures the deviation of a particular provider's workload on a given day from their average daily workload. We construct the provider demeaned workload by first generating a monthly mean of the number of daily visits for each provider, and then subtracting this mean from the actual number of visits conducted on a particular day. Therefore, days in which a provider visits fewer patients than average would yield a negative value for demeaned workload, and days in which a provider visits more patients than average would yield a positive value for demeaned workload.

We use a two-stage least squares (2SLS) strategy, with the following first-stage equation:

$$demeaned\_visitlength_{ijt} = \alpha + \gamma \cdot order_{ijt} + \delta \cdot demeaned\_workload_{jt} + \mathbf{X}_i + \theta_t + W_j + \phi_{ijt} \quad (2)$$

Here, $order_{ijt}$ is the order of visit i by provider j at time t, and $demeaned\_workload_{jt}$ is the demeaned workload of provider j at time t. Using the predicted value of $demeaned\_visitlength_{ijt}$ from the first-stage equation, we then estimate the following second-stage equation:

$$R_{ijt} = \alpha + \beta_{IV} \cdot \widehat{demeaned\_visitlength}_{ijt} + \mathbf{X}_i + \theta_t + W_j + \epsilon_{ijt} \quad (3)$$

Here, the β_{IV} is the selection-corrected 2SLS estimator of the impact of the demeaned length of a home health visit on hospital readmission.

For these instruments to be valid and provide unbiased estimates, two conditions must be satisfied (Wooldridge 2010). First, each of the instruments must be relevant, in that they are correlated with the demeaned length of a home health visit. We test this assumption by examining the F-statistic against the null that the instruments are not relevant. We report these results in section 5.2.

When examining each of the instruments separately, we find that our first instrument, visit order, is negatively correlated with the outcome measure, the demeaned visit length. In other words, patients who are visited later in the day of a provider's schedule for the day are more likely to experience shorter than average home health visits. This is consistent with prior literature on the effects of scheduling on the speed and quality of work in discretionary service settings. In the context of food safety inspections, Ibanez and Toffel (2017) find that inspectors cite fewer violations for establishments they visit later in the day (i.e., have a higher visit order), and that this is especially the case when they are at risk of prolonging their scheduled shift. There is also a negative correlation between our second instrument, the provider demeaned workload, and the demeaned visit length. This illustrates that patients who are visited by a provider who is experiencing a higher than typical workload are more likely to experience shorter than average home health visits. We also find this relationship to be consistent with prior literature. In studies across several settings, operations management scholars find that when workers experience higher than typical levels of workload, they will reduce their effort (KC and Terwiesch 2009, Tan and Netessine 2014) and deliver lower of levels of quality (Berry Jaeker and Tucker 2017), which may lead to lower revenue and other negative financial consequences (Powell et al. 2012).

As a second condition, each of the instruments must satisfy the exclusion restriction. In other words, visit order and workload should affect a patient's risk of readmission only through their effects on the amount of time the home health provider spends with a patient during the home health visit. Though it is not possible to test this assumption directly, certain operational aspects of the home health agency provide support for this assumption. At the home health agency from which we obtained these data, the order in which a provider is to visit patients on a given day is determined by taking the patients to whom a provider has been assigned to visit that day (which is determined by the central office) and mapping out their locations to chart a course that minimizes the geographic distance to be traveled by the provider. In other words, the order in which a patient was visited on a particular day is independent of his/her illness severity. In addition, a provider's workload on a given day tends to be a function of how many hours the provider is scheduled to work that day and the total geographic distance to be traveled based on the locations of the visits. Hence, the demeaned workload of a provider on a given day is also uncorrelated with a particular patient's illness severity. Thus, with each of our instruments, we can exploit the fact that visit order and demeaned workload affect the risk of readmission only through their effects on the demeaned visit length, and are otherwise uncorrelated with other factors related to hospital readmission and, thus, the error term, ϵ_{ijt}.

5.2. Instrumental variable estimation results

Table 3 reports the first-stage results from estimating equation (2), in which we estimate the effect of visit order and demeaned provider workload conditional on the patient- and provider-level observable characteristics described above. We find visit order to be negatively associated with the demeaned visit length, and this relationship is especially strong when we fully saturate the model with demographic controls, the start hour of the provider's work day, and the average length of the patient's prior home health visits ($\gamma = -0.13492$, $p < 0.01$). This indicates that visits performed later in the day tend to be shorter than the average visit, relative to the average length of visit during a patient's home health episode. Specifically, we find that a one standard deviation change in visit order is associated with a decrease in demeaned visit length of 13 seconds.

We also find the provider demeaned workload to be strongly negatively associated with the demeaned visit length ($\delta = -0.63034$, $p < 0.001$ in the fully saturated model). This suggests that when a visit is performed by provider who is busier than usual, the visit tends to be shorter than

Table 3 Predicted demeaned visit length (2SLS first stage)

	(1)	(2)	(3)	(4)
Visit order	-0.04754	-0.06639	-0.08474+	-0.13492**
	(0.04094)	(0.04300)	(0.04332)	(0.04406)
Demeaned workload	-0.88675***	-0.86293***	-0.92690***	-0.63034***
	(0.04869)	(0.05127)	(0.05261)	(0.04963)
Hospitalization reasons	Y	Y	Y	Y
High risk factors	Y	Y	Y	Y
Living conditions	Y	Y	Y	Y
Risks for hospitalization	Y	Y	Y	Y
Health status	Y	Y	Y	Y
Other health conditions	Y	Y	Y	Y
Demographic controls		Y	Y	Y
Workday start hour			Y	Y
Moving average visit length				Y
Visit number FE	Y	Y	Y	Y
Provider FE	Y	Y	Y	Y
Observations	61,344	55,172	55,171	55,171
R-squared	0.27804	0.30847	0.30878	0.40622

Notes. Columns (1)-(4) are fixed effects linear regression models estimated at the home health visit level. In all columns, we control for prior hospitalization reasons (dummies for disruptive behavior, impaired decision making, indwelling catheter, intractable pain, memory loss, urinary incontinence, unknown, and none of the above), high risk factors (dummies for alcohol dependency, drug dependency, smoking, and obesity), living conditions (dummies for having no assistance available and for living alone), risk factors for hospitalization (dummies for 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), health status (progressively worse (patient has serious progressive conditions that could lead to death within a year), temporarily heightened (temporarily facing high health risks), stable (patient is likely to remain in fragile health)), and other health conditions (dummies for diabetes, mental disorders, and other), visit number fixed effects, and provider fixed effects. In columns (2)-(4), demographic controls include dummies for age, male, Black, White, Asian, and Hispanic. In columns (3)-(4), we also control for the start hour of the provider's work day. In column (4), we also control for the average visit length of a patient's home health visits before visit i within the same home health episode. Robust standard errors (in parentheses) allow for arbitrary correlation within a given home health episode. $+p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

the average visit length. Specifically, a one standard deviation change in demeaned workload is associated with a decrease in demeaned visit length of 49 seconds.

Together, given a fully saturated model (column (4)), we find the two instruments to be strong joint predictors of the endogenous regressor. The Kleibergen-Paap Wald rk F statistic is large ($F = 120$), which supports this notion that our instruments are not weak, despite the seemingly small magnitude of the associations.[7] As such, we can interpret Table 3 to conclude that visits performed later in the day and by busier than usual providers tend to be shorter in duration than the average visit for a patient during his/her home health episode.

[7] Unlike the Cragg-Donald Wald F statistic, the Kleibergen-Paap Wald rk F statistic allows us to account for non-i.i.d. errors consistent with our clustered standard errors (Kleibergen and Paap 2006, Staiger and Stock 1997).

Table 4 Effect of predicted demeaned visit length on readmission (2SLS second stage)

	(1)	(2)	(3)	(4)
Demeaned visit length	-0.00110*	-0.00121*	-0.00122*	-0.00164*
	(0.00048)	(0.00055)	(0.00055)	(0.00075)
Hospitalization reasons	Y	Y	Y	Y
High risk factors	Y	Y	Y	Y
Living conditions	Y	Y	Y	Y
Risks for hospitalization	Y	Y	Y	Y
Health status	Y	Y	Y	Y
Other health conditions	Y	Y	Y	Y
Demographic controls		Y	Y	Y
Workday start hour			Y	Y
Moving average visit length				Y
Visit number FE	Y	Y	Y	Y
Provider FE	Y	Y	Y	Y
Observations	61,227	55,050	55,049	55,049

Notes. Columns (1)-(4) are fixed effects linear probability models estimated at the home health visit level. In all columns, we control for prior hospitalization reasons (dummies for disruptive behavior, impaired decision making, indwelling catheter, intractable pain, memory loss, urinary incontinence, unknown, and none of the above), high risk factors (dummies for alcohol dependency, drug dependency, smoking, and obesity), living conditions (dummies for having no assistance available and for living alone), risk factors for hospitalization (dummies for 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), health status (progressively worse (patient has serious progressive conditions that could lead to death within a year), temporarily heightened (temporarily facing high health risks), stable (patient is likely to remain in fragile health)), and other health conditions (dummies for diabetes, mental disorders, and other), visit number fixed effects, and provider fixed effects. In columns (2)-(4), demographic controls include dummies for age, male, Black, White, Asian, and Hispanic. In columns (3)-(4), we also control for the start hour of the provider's work day. In column (4), we also control for the average visit length of a patient's home health visits before visit i within the same home health episode. Robust standard errors (in parentheses) allow for arbitrary correlation within a given home health episode. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

In Table 4, we report the second-stage estimation results of regressing the indicator for hospital readmission (at the visit level) on the predicted demeaned value of visit length ($\widehat{demeaned\_visitlength}_{ijt}$; see equation (3)). To account for the high dimensionality and multiple levels of fixed effects, we use a high-dimensional multi-way fixed effect model suggested by Correia (2017). Again, we present four specifications in which we gradually saturate the model further with additional controls for patient demographics, the start hour of the provider's work day, and the average length of home health visits before visit i. We find that the main coefficient of interest for the demeaned visit length (β_{IV}) is stable across all four specifications (Table 4). In general, we find that longer than average visits decrease the likelihood of hospital readmission in a statistically significant way, with the magnitude of this effect being nearly four times that of the effect estimated using the OLS approach (Table 2). Put differently, shorter than average visits increase the likelihood of hospital readmission. Specifically, the fully saturated model (column (4)) shows that one extra minute relative to the average visit length decreases the probability of hospital readmission by 0.164 percentage points ($p < 0.05$). Given 2 percent of home health visits are followed by a hospital readmission on average (Table 1a), this indicates that the one extra minute relative to the average visit length is associated with an 8 percent decrease in the likelihood of hospital readmission.

5.3. Potential mechanisms underlying the effect on readmissions

To better understand what might be driving this effect of visit length on hospital readmission, we explore two potential mechanisms that may also serve as managerial levers: (a) the full-time versus part-time status of home health providers, and (b) the clinical role of home health providers.

Table 5 Effect of predicted demeaned visit length on readmission, full time v. part time providers (2SLS second stage)

	A. Full-time providers				B. Part-time providers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Demeaned visit length	-0.00057	-0.00057	-0.00052	-0.00064	-0.00187**	-0.00210**	-0.00208**	-0.00312**
	(0.00074)	(0.00081)	(0.00079)	(0.00101)	(0.00066)	(0.00075)	(0.00078)	(0.00120)
Hospitalization reasons	Y	Y	Y	Y	Y	Y	Y	Y
High risk factors	Y	Y	Y	Y	Y	Y	Y	Y
Living conditions	Y	Y	Y	Y	Y	Y	Y	Y
Risks for hospitalization	Y	Y	Y	Y	Y	Y	Y	Y
Health status	Y	Y	Y	Y	Y	Y	Y	Y
Other health conditions	Y	Y	Y	Y	Y	Y	Y	Y
Demographic controls		Y	Y	Y		Y	Y	Y
Workday start hour			Y	Y			Y	Y
Moving average visit length				Y				Y
Visit number FE	Y	Y	Y	Y	Y	Y	Y	Y
Provider FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	33,196	30,129	30,129	30,129	22,860	20,446	20,446	20,446

Notes. Columns (1)-(8) are fixed effects linear probability models estimated at the home health visit level. In all columns, we control for prior hospitalization reasons (dummies for disruptive behavior, impaired decision making, indwelling catheter, intractable pain, memory loss, urinary incontinence, unknown, and none of the above), high risk factors (dummies for alcohol dependency, drug dependency, smoking, and obesity), living conditions (dummies for having no assistance available and for living alone), risk factors for hospitalization (dummies for 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), health status (progressively worse (patient has serious progressive conditions that could lead to death within a year), temporarily heightened (temporarily facing high health risks), stable (patient is likely to remain in fragile health)), and other health conditions (dummies for diabetes, mental disorders, and other), visit number fixed effects, and provider fixed effects. In columns (2)-(4) and (6)-(8), demographic controls include dummies for age, male, Black, White, Asian, and Hispanic. In columns (3)-(4) and (7)-(8), we also control for the start hour of the provider's work day. In columns (4) and (8), we also control for the average visit length of a patient's home health visits before visit i within the same home health episode. Robust standard errors (in parentheses) allow for arbitrary correlation within a given home health episode. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

The first potential mechanism is the full-time versus part-time status of home health providers. In our sample, about 54 percent of providers are full time, and about 37 percent are part time. There are a number of reasons to expect differential effects between the full-time and the part-time providers. First, full-time providers are likely to have more stable visit schedules, leading to more efficient time management. Part-time providers may be more likely to receive a last-minute visit request, which may lead to unexpected changes to their daily visit schedules. Second, part-time providers are also more likely to stint on the length of a visit if they have other employment commitments to fulfill as well. Relative to full-time providers, they have higher levels of discretion in their time management.

In Table 5, we report the 2SLS second-stage results from estimating equation (3) on a subsample of visits conducted by full-time providers (Panel A) and part-time providers (Panel B). The results show that the effect of the demeaned visit length on hospital readmission is wholly driven by part-time providers. When considering only visits provided by full-time providers, we find no significant effect of the demeaned visit length on readmission likelihood in the fully saturated model ($\beta_{IV} = -0.00064$, $p \approx 0.5$). However, looking at visits provided by part-time providers, we find a significant effect on readmission in the fully saturated model ($\beta_{IV} = -0.00312$, $p < 0.01$). The magnitude of this coefficient is approximately double that of the corresponding coefficient when combining all providers (Table 4 column (4)). Accounting for the fact that the likelihood of a home health visit resulting in a hospital readmission remains at 2 percent across both subsamples, this suggests that an extra minute during a home health visit with a part-time provider (relative to the average visit length) is associated with a 16 percent decrease in the likelihood of hospital readmission.

We also explore whether the effect of demeaned visit length on readmissions may be driven by home health providers serving particular clinical roles. As we discuss in section 3.1, there are various types of home health providers, each of which serves a different clinical role. In Table 1a, we see that the majority of home health visits are provided by registered nurses (RNs) and physical therapists (PTs). These two provider types deliver very different services. RNs administer skilled nursing care to patients in accordance with the prescribing physician's orders and the established plan of care. Their responsibilities include the initial evaluation and reevaluation of a patient's continuous nursing needs, home health services coordination (including referrals to therapists or medical social workers, as needed), communication with physicians regarding changes in a patient's condition, and communication with the patient's family regarding continuing home health care needs. On the other hand, PTs evaluate and treat patients suffering from a physical disability using exercises, hands-on therapy, and equipment that helps reduce pain and improves mobility, all in accordance with the established care plan. As such, while RNs exercise a significant amount of discretion in their care provision, PTs have a much more limited level of discretion that they can exercise.

This difference in worker discretion may imply that changes in the length of a home health visit performed by an RN as opposed to a PT will have different, and perhaps more significant, effects on a patient's risk of an unplanned hospital readmission. Since PTs follow an established care plan, they may not have as much of an opportunity to deviate from the usual visit duration. More importantly, since RNs are the contact point for patients to express their concerns regarding changes in their health status, patients may be more likely to initiate an unplanned hospital visit if they believe that the RN did not address all of their concerns due to a shorter than usual visit length.

Table 6 Effect of predicted demeaned visit length on readmission, RNs v. PTs (2SLS second stage)

	A. Registered nurse				B. Physical therapist			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Demeaned visit length	-0.00088	-0.00117	-0.00158^{+}	-0.00318^{+}	-0.00001	0.00022	0.00065	0.00060
	(0.00071)	(0.00085)	(0.00088)	(0.00168)	(0.00098)	(0.00106)	(0.00105)	(0.00117)
Hospitalization reasons	Y	Y	Y	Y	Y	Y	Y	Y
High risk factors	Y	Y	Y	Y	Y	Y	Y	Y
Living conditions	Y	Y	Y	Y	Y	Y	Y	Y
Risks for hospitalization	Y	Y	Y	Y	Y	Y	Y	Y
Health status	Y	Y	Y	Y	Y	Y	Y	Y
Other health conditions	Y	Y	Y	Y	Y	Y	Y	Y
Demographic controls		Y	Y	Y		Y	Y	Y
Workday start hour			Y	Y			Y	Y
Moving average visit length				Y				Y
Visit number FE	Y	Y	Y	Y	Y	Y	Y	Y
Provider FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	23,625	20,954	20,954	20,954	22,826	21,132	21,131	21,131

Notes. Columns (1)-(8) are fixed effects linear probability models estimated at the home health visit level. In all columns, we control for prior hospitalization reasons (dummies for disruptive behavior, impaired decision making, indwelling catheter, intractable pain, memory loss, urinary incontinence, unknown, and none of the above), high risk factors (dummies for alcohol dependency, drug dependency, smoking, and obesity), living conditions (dummies for having no assistance available and for living alone), risk factors for hospitalization (dummies for 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), health status (progressively worse (patient has serious progressive conditions that could lead to death within a year), temporarily heightened (temporarily facing high health risks), stable (patient is likely to remain in fragile health)), and other health conditions (dummies for diabetes, mental disorders, and other), visit number fixed effects, and provider fixed effects. In columns (2)-(4) and (6)-(8), demographic controls include dummies for age, male, Black, White, Asian, and Hispanic. In columns (3)-(4) and (7)-(8), we also control for the start hour of the provider's work day. In columns (4) and (8), we also control for the average visit length of a patient's home health visits before visit i within the same home health episode. Robust standard errors (in parentheses) allow for arbitrary correlation within a given home health episode. $+p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

In Table 6, we report the 2SLS second-stage results from estimating equation (3) on a subsample of visits conducted by RNs (Panel A) and PTs (Panel B). For visits provided by PTs, we find no significant effect of the demeaned visit length on readmission likelihood ($\beta_{IV} = -0.00060$, $p \approx 0.61$ in the fully saturated model). On the other hand, we find there is a marginally significant effect of the demeaned visit length on hospital readmission when considering only visits provided by RNs ($\beta_{IV} = -0.00318$, $p \approx 0.059$ in the fully saturated model). Similar to what we saw for part-time providers' visits above, the magnitude of this coefficient is approximately double that of the corresponding coefficient when combining all providers (Table 4 column (4)). Given home health visits by RNs have a slightly higher average likelihood of resulting in a hospital readmission (2.5 percent), this shows that an extra minute during an RN home health visit (relative to the average visit length) is associated with a 13 percent decrease in the likelihood of hospital readmission.

6. Robustness checks

To examine the robustness of our main findings, we conduct a number of additional analyses. Specifically, we relax several restrictions imposed in defining our main analysis sample (section 3.2) and explore how this affects our findings. The results from these additional analyses are shown in the Appendix.

We begin by relaxing the restriction of excluding visits that happened on days in which a patient received more than one home health care visit on a given day. We expect this to marginally dilute our effects, since a readmission could have been the result of one of the two or more visits. Using this sample that now includes multi-visit days, we present the results of the OLS approach in addition to the first- and second-stages of the 2SLS approach in Table A1. In the OLS specification, we find similar trends and a slight decrease in the magnitude of the coefficients. The fully saturated first-stage results again show that visit order and demeaned workload have a significant effect on the demeaned visit length. These coefficients are also similar to our main results, although slightly smaller in magnitude. The second-stage results produce a similar set of findings to our main results, both in directionality and magnitude. As such, we find that including multi-visit days minimally affects our main results.

Next, we repeat our analyses on a sample that includes all patients regardless of whether or not they had a condition subject to a readmission penalty under the HRRP. This allows us to look at a more general patient population that is referred to home health from inpatient hospitals, as opposed to a sicker subsample of patients who are referred with conditions that are targeted by the HRRP. As such, we expect the effects to be weaker since this sample is potentially less acute than the HRRP sample. For this sample with all patients, we present the results of the OLS approach in addition to the first- and second-stages of the 2SLS approach in Table A2. Across both specifications, we find results that are similar to our main results, albeit with coefficients of slightly smaller magnitude. Specifically, given 1.7 percent of home health visits are followed by a hospitalization in this sample, we find that an extra minute relative to the average length of a patient's home health visits reduces their readmission likelihood by approximately 5 percent. This suggests that patients with HRRP-targeted conditions may be more sensitive to shorter than usual home health visit lengths.

Finally, we use an alternate definition of recertifications in conducting our analyses. Some episodes in our sample are not flagged as recertifications by the home health agency but may be considered recertifications, as they began less than 60 days after the initial home health visit for the patient. As such, we repeat our analyses using an alternate definition of recertification, in which we consider any episode with a start date that is less than 60 days after the start date of the initial visit as a recertification. Then, as we describe in section 3.2, we exclude these recertificiations from our analysis sample and rerun the analyses. We present these results in Table A3, and find our main results to be robust to this alternate definition of recertifications.

7. Discussion and conclusions

As health care spending in the U.S. continues to grow, policymakers and practitioners are seeking to find ways to better manage expenditures. With hospital care comprising the largest proportion of spending (Centers for Medicare & Medicaid Services 2018b), one approach that has garnered significant attention is reducing the number of avoidable or excessive hospital readmissions. With the introduction of readmission penalties via the HRRP and the growing emphasis on population health management, home health care has become a key avenue for enhancing the continuity of care following discharge from a hospital. Most importantly, it allows hospitals to oversee the care of patients and monitor their recovery after discharge.

Understanding how home health functions and potentially impacts a patient's likelihood of readmission is crucial for achieving these goals. Some recent work has focused on understanding how care discontinuity in the home health setting may affect hospital readmissions, finding that handoffs among home health providers (a proxy for care discontinuity) is associated with a significant increase in the likelihood of hospital readmission (David and Kim 2017). In our study, we turn our focus to the amount of time a home health provider spends with a patient during a visit, as we seek to understand how the length of a post-discharge provider-patient interaction may impact the likelihood of hospital readmission. In doing so, we are able to examine the nature of speed-quality tradeoffs in a multistage service process. To address the identification challenge arising from the endogeneous nature of the length of a home health visit, we leverage an instrumental variable approach using two instruments: visit order and deviation from typical provider workload.

Our results underscore the significant role that home health providers may play in influencing the likelihood of hospital readmission, especially among patients with conditions that are subject to penalty under the HRRP. For these patients, we find that an extra minute relative to the average length of their typical home health visits reduces their likelihood of readmission by approximately 8 percent. This effect seems to be driven by part-time providers rather than full-time providers; looking at part-time providers in isolation, we find that an extra minute during a home health visit with them is associated with a 16 percent decrease in the likelihood of hospital readmission. When considering visits by providers with high levels of discretion (e.g., RNs) versus low levels of discretion (e.g., PTs), we find that the effect is more pronounced among the former group; an extra minute (relative to the average visit length) during an RN home health visit is associated with a 13 percent decrease in hospital readmission likelihood. When considering all patients, as opposed to only those with a target condition, we find that an extra minute relative to the average length of a patient's home health visit reduces the readmission likelihood by approximately 5 percent.

Altogether, our findings suggest that there may be considerable benefits to a slightly longer than average home health visit, especially when the visit is conducted by a part-time provider or an RN, and particularly among patients with target conditions. In other words, by finding ways to avoid cutting short post-acute home health visits, we may be able to reduce the risk of hospital readmissions in a meaningful way.

7.1. Managerial implications

While slightly longer home health visits may have the benefit (and cost savings) of reducing hospital readmissions, there are also costs associated with the additional capacity investments. As such, we consider whether, on balance, there may be a cost savings associated with increasing the amount of time spent with a home health provider.

To address this question, let us revisit the baseline statistics on the supply and demand of home health visits. On average, each region in our sample has 6 offices with a total of 30 RNs conducting home health visits on a given day. Each RN conducts 4.20 visits per day spending 42.07 minutes with each patient. If we assume that a region employs one additional RN per day while keeping the total number of patients to be visited on a given day constant, each RN can reduce her average daily number of visits from 4.20 to 4.06. Given this reduction in the average number of visits per day, each RN could increase the average amount of time spent with a patient per visit from 42.07 minutes to 43.47 minutes, or by approximately 1.40 minutes. Based on our results from section 5.3, which indicate that an extra minute during a home health visit with an RN is associated with a 0.318 percentage point decrease in hospital readmission likelihood, we can infer that the 1.40-minute increase in time spent during a home health visit could lead to a 0.45 percentage point decrease in readmission likelihood. Given the 2.5 percent average likelihood of RN home health visits resulting in a hospital readmission at baseline, this corresponds to a 17.8 percent decrease in readmission likelihood. Since the average cost of a hospital readmission is approximately $13,800 (Barrett et al. 2015), this decrease translates into a $7,737 cost savings to the hospital from the reduced risk of unplanned readmissions. We can then compare this to additional capacity investment on the part of the home health agency. Given the $27.10 per hour in wages earned by RNs at this home health agency and an average daily workload of 176.70 minutes per RN, it would cost the home health agency as little as $80 (assuming hourly pay and no compensation for transport time or benefits) to as much as $280 (assuming compensation for an 8-hour work day and 30% of salary in benefits) per day to employ one additional RN across the region. On balance, this suggests that the cost of investing in additional home health capacity is outweighed by the cost savings arising from fewer hospitalizations.

Of course, due to the multistage nature of the post-acute care process and the fact that capacity investments are made at one stage whereas cost savings are reaped at another, it is important to consider ways to align incentives between the different stages. One possibility is to formulate alternate payment schemes, similar to those proposed in Guajardo et al. (2012). For example, one potential performance-based contract may levy part of the readmission penalty on the home health agency as well (as opposed to only on the hospital). Alternatively, there may be a contract between the hospital and the home health agency, in which the hospital subsidizes a portion of the costs incurred by the home health agency. Another approach is to vertically integrate the hospital and the home health agency, as a way to align incentives and internalize costs. Although the home health agency in our study is a free-standing one that is not integrated with a hospital or a hospital system, some prior work illustrates that there may be benefits to such an approach. For example, David et al. (2013) demonstrate that vertical integration may allow hospitals to shift certain tasks downstream to home health agencies, such that patients can be discharged earlier and receive more intensive post-acute care. The authors find that this can be attained at an overall lower cost to the system and without compromising health outcomes.

Rather than investing in greater capacity or devising contractual approaches for aligning incentives, one might also identify ways to more efficiently allocate the existing capacity by reorganizing the home health workforce, restructuring its workload, and reprioritizing its operations. For example, given the length of a home health visit seems to be affected by the sequence of visits on a given day, home health agencies should strive to schedule visits for patients who are at a higher risk of readmission earlier in a provider's workday. In addition, when developing the visit schedules for each provider, home health agencies may choose to assign patients to providers based on their severity and risk of deterioration as opposed to their geographical proximity to one another in an attempt to minimize driving time. In particular, if agencies restructure provider daily workload such that it is negatively correlated with patients' levels of severity, this would allow providers to spend more time with patients who are at a higher risk of readmission. Home health agencies may also choose to engage in provider specialization, where some providers specialize in seeing patients with more complex conditions, while others specialize in cases of low urgency and low propensity for readmissions. Given this type of arrangement, providers who specialize in higher severity cases could be assigned fewer visits per day, which would allow them to spend more time with each of their patients. At the same time, those who specialize in cases with a lower risk of hospital readmission could maintain a higher daily volume of visits, where each visit could be relatively shorter without compromising on quality. Unlike the current geographically-based provider-patient assignment system (where providers are scheduled to visit patients based on their geographic colocation), this severity-based provider-patient assignment system would prioritize the matching of patients to providers based on their severity and risk of readmission.

7.2. Limitations and future research

Our work is not without limitations, and its results should be interpreted accordingly. First, although we have a rich proprietary dataset that details many operational aspects of home health visits, the data do not contain information about exactly what tasks the home health provider performed (or did not perform) during the visit. As a result, we have limited insight into how or why a shorter visit may lead to an increased risk of hospital readmission. If such data are available in other settings, future work should examine variation in within-visit tasks to better understand the mechanisms underlying the effects identified in this study.

Second, though our data allow us to distinguish between planned and unplanned hospital readmissions, we are unable to determine whether a particular readmission was clinically warranted or not. As a result, we are not in a position to make inferences about whether longer than usual home health visits may reduce the likelihood of *unnecessary* (as opposed to unplanned) hospital readmissions. Nevertheless, our approach of studying the effects on unplanned readmissions is in line with how the HRRP determines penalties, as the HRRP also does not seek to distinguish necessary versus unnecessary readmissions.

7.3. Conclusions

In recent years, the utilization of the post-acute home health care services has been on the rise, with the hopes that better coordination of post-discharge care will help reduce costly unplanned hospital readmissions. In this study, we seek to develop a deeper understanding of how and through which operational levers home health care may be able to reduce the likelihood of hospital readmissions. We find evidence to support the notion that shortening provider-patient interactions in a home health setting may have negative consequences in the form of an increased risk of hospital readmissions. As such, we argue that careful time management and allocation by home health providers is essential to improving the quality of care. Future work should concentrate on identifying other aspects of the home health operations that can be leveraged to reduce hospital readmissions.

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Appendix

Table A1 Effect of demeaned visit length on readmission, including multi-visit days

	(1)	(2)	(3)	(4)
OLS				
Demeaned visit length	-0.00030***	-0.00034***	-0.00034***	-0.00039***
	(0.00004)	(0.00004)	(0.00004)	(0.00005)
Observations	85,398	77,635	77,634	77,634
R-squared	0.03313	0.03721	0.03721	0.03737
2SLS First stage				
Visit order	-0.01473	-0.02053	-0.03825	-0.08117*
	(0.03526)	(0.03688)	(0.03710)	(0.03866)
Demeaned workload	-0.79037***	-0.77687***	-0.84097***	-0.60936***
	(0.04058)	(0.04242)	(0.04388)	(0.04234)
Observations	85,398	77,635	77,634	77,634
R-squared	0.25302	0.27688	0.27718	0.35526
2SLS Second stage				
Demeaned visit length	-0.00097*	-0.00113*	-0.00121*	-0.00162*
	(0.00046)	(0.00051)	(0.00050)	(0.00066)
Observations	85,301	77,530	77,529	77,529
Hospitalization reasons	Y	Y	Y	Y
High risk factors	Y	Y	Y	Y
Living conditions	Y	Y	Y	Y
Risks for hospitalization	Y	Y	Y	Y
Health status	Y	Y	Y	Y
Other health conditions	Y	Y	Y	Y
Demographic controls		Y	Y	Y
Workday start hour			Y	Y
Moving average visit length				Y
Visit number FE	Y	Y	Y	Y
Provider FE	Y	Y	Y	Y

Notes. Columns (1)-(4) are estimated at the home health visit level. OLS, and 2SLS first stage, and 2SLS second stage models are estimated separately, although the results are shown in the same column for ease of presentation. In all columns, we control for prior hospitalization reasons (dummies for disruptive behavior, impaired decision making, indwelling catheter, intractable pain, memory loss, urinary incontinence, unknown, and none of the above), high risk factors (dummies for alcohol dependency, drug dependency, smoking, and obesity), living conditions (dummies for having no assistance available and for living alone), risk factors for hospitalization (dummies for 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), health status (progressively worse (patient has serious progressive conditions that could lead to death within a year), temporarily heightened (temporarily facing high health risks), stable (patient is likely to remain in fragile health)), and other health conditions (dummies for diabetes, mental disorders, and other), visit number fixed effects, and provider fixed effects. In columns (2)-(4), demographic controls include dummies for age, male, Black, White, Asian, and Hispanic. In columns (3)-(4), we also control for the start hour of the provider's work day. In column (4), we also control for the average visit length of a patient's home health visits before visit i within the same home health episode. Robust standard errors (in parentheses) allow for arbitrary correlation within a given home health episode. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A2 Effect of demeaned visit length on readmission, including non-target conditions

	(1)	(2)	(3)	(4)
OLS				
Demeaned visit length	-0.00027***	-0.00030***	-0.00030***	-0.00034***
	(0.00001)	(0.00002)	(0.00002)	(0.00002)
Observations	564,978	512,327	512,321	512,321
R-squared	0.01167	0.01357	0.01357	0.01365
2SLS First stage				
Visit order	-0.02712*	-0.04016**	-0.06254***	-0.07171***
	(0.01356)	(0.01435)	(0.01451)	(0.01509)
Demeaned workload	-0.85976***	-0.83046***	-0.92007***	-0.66447***
	(0.01642)	(0.01739)	(0.01864)	(0.01838)
Observations	564,978	512,327	512,321	512,321
R-squared	0.23887	0.26500	0.26554	0.35966
2SLS Second stage				
Demeaned visit length	-0.00064***	-0.00079***	-0.00068***	-0.00087***
	(0.00015)	(0.00017)	(0.00016)	(0.00022)
Observations	564,878	512,240	512,234	512,234
Hospitalization reasons	Y	Y	Y	Y
High risk factors	Y	Y	Y	Y
Living conditions	Y	Y	Y	Y
Risks for hospitalization	Y	Y	Y	Y
Health status	Y	Y	Y	Y
Other health conditions	Y	Y	Y	Y
Demographic controls		Y	Y	Y
Workday start hour			Y	Y
Moving average visit length				Y
Visit number FE	Y	Y	Y	Y
Provider FE	Y	Y	Y	Y

Notes. Columns (1)-(4) are estimated at the home health visit level. OLS, and 2SLS first stage, and 2SLS second stage models are estimated separately, although the results are shown in the same column for ease of presentation. In all columns, we control for prior hospitalization reasons (dummies for disruptive behavior, impaired decision making, indwelling catheter, intractable pain, memory loss, urinary incontinence, unknown, and none of the above), high risk factors (dummies for alcohol dependency, drug dependency, smoking, and obesity), living conditions (dummies for having no assistance available and for living alone), risk factors for hospitalization (dummies for 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), health status (progressively worse (patient has serious progressive conditions that could lead to death within a year), temporarily heightened (temporarily facing high health risks), stable (patient is likely to remain in fragile health)), and other health conditions (dummies for diabetes, mental disorders, and other), visit number fixed effects, and provider fixed effects. In columns (2)-(4), demographic controls include dummies for age, male, Black, White, Asian, and Hispanic. In columns (3)-(4), we also control for the start hour of the provider's work day. In column (4), we also control for the average visit length of a patient's home health visits before visit i within the same home health episode. Robust standard errors (in parentheses) allow for arbitrary correlation within a given home health episode. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A3 Effect of demeaned visit length on readmission, using alternate definition of recertifications

	(1)	(2)	(3)	(4)
OLS				
Demeaned visit length	-0.00031***	-0.00036***	-0.00036***	-0.00042***
	(0.00005)	(0.00005)	(0.00005)	(0.00006)
Observations	61,134	54,971	54,970	54,970
R-squared	0.04224	0.04674	0.04674	0.04693
2SLS First stage				
Visit order	-0.04782	-0.06817	-0.08672*	-0.13770**
	(0.04098)	(0.04305)	(0.04337)	(0.04412)
Demeaned workload	-0.88494***	-0.86046***	-0.92506***	-0.62946***
	(0.04874)	(0.05132)	(0.05268)	(0.04969)
Observations	61,134	54,971	54,970	54,970
R-squared	0.27829	0.30879	0.30909	0.40661
2SLS Second stage				
Demeaned visit length	-0.00107*	-0.00118*	-0.00117*	-0.00157*
	(0.00049)	(0.00055)	(0.00055)	(0.00075)
Observations	61,016	54,847	54,846	54,846
Hospitalization reasons	Y	Y	Y	Y
High risk factors	Y	Y	Y	Y
Living conditions	Y	Y	Y	Y
Risks for hospitalization	Y	Y	Y	Y
Health status	Y	Y	Y	Y
Other health conditions	Y	Y	Y	Y
Demographic controls		Y	Y	Y
Workday start hour			Y	Y
Moving average visit length				Y
Visit number FE	Y	Y	Y	Y
Provider FE	Y	Y	Y	Y

Notes. Columns (1)-(4) are estimated at the home health visit level. OLS, and 2SLS first stage, and 2SLS second stage models are estimated separately, although the results are shown in the same column for ease of presentation. In all columns, we control for prior hospitalization reasons (dummies for disruptive behavior, impaired decision making, indwelling catheter, intractable pain, memory loss, urinary incontinence, unknown, and none of the above), high risk factors (dummies for alcohol dependency, drug dependency, smoking, and obesity), living conditions (dummies for having no assistance available and for living alone), risk factors for hospitalization (dummies for 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), health status (progressively worse (patient has serious progressive conditions that could lead to death within a year), temporarily heightened (temporarily facing high health risks), stable (patient is likely to remain in fragile health)), and other health conditions (dummies for diabetes, mental disorders, and other), visit number fixed effects, and provider fixed effects. In columns (2)-(4), demographic controls include dummies for age, male, Black, White, Asian, and Hispanic. In columns (3)-(4), we also control for the start hour of the provider's work day. In column (4), we also control for the average visit length of a patient's home health visits before visit i within the same home health episode. Robust standard errors (in parentheses) allow for arbitrary correlation within a given home health episode. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.