Staff Level and Healthcare Access Equality in Long-Term Care Settings: Evidence from Regulation on Mandatory Nurses Overtime

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Abstract

Nursing homes typically keep a limited formal nurse staff level and rely on overtime hours and contract nurse hours during demand peak because of uncertainty in future patient volume and required healthcare services. I leverage on U.S. state level regulations restricting nurse overtime hours as exogenous negative shock to nursing home's ability use overtime hours to estimate the staffing decision response of nursing homes and the consequential change in patient composition in terms of payment source. Consistent with past literature, nursing homes in states restricting overtime hours reduced total hours from formal nurse staff by 2.7 percent. The proportion of Medicaid patients increased by around 1 percentage point as the increased reliance on contract nurses increased marginal labor cost of treating Medicare patients, who are typically discharged from acute care settings and thus with more uncertainty in arrival rate and health status. My results highlight the linkage between composition of health provider's labor input and patient types. Policy makers should account for this linkage that could incur side effects for labor regulations or policies promoting healthcare access.

1 Introduction

The disadvantageous access to quality care faced by Medicaid patients has been a persistent concern among policy makers and academia. Survey study by Medicaid and CHIP Payment and Access Commission (MACPAC) in 2019 shows that providers are much less likely to accept new patients covered by Medicaid (70.8 percent) compared to patients covered by Medicare (85.3 percent) or private insurance (90 percent) [38]. Given the substantially lower reimbursement rate of Medicaid compared to Medicare for long-term care expenses, nursing homes facing capacity constraint may either refuse to admit Medicaid patients or discharge them at a faster pace to avoid the high opportunity cost. Although the selection behavior has been well documented in hospital and physician office industry (e.g. [14], [19], [47]), the empirical investigation in long-term care settings only began to grow in recent years and remains incomplete in in understanding of mechanism driving the selective admission. Past literature on nursing home's fixed capacity constraint measured in beds and the large reimbursement difference between Medicare and Medicaid. In this paper I investigate the relationship between nursing home's nurse staff level and patient composition to explore role of labor regulation as a potential solution to the patient cherry-picking in healthcare industry.

There are several reasons that labor cost can affect patient selection behavior of nursing homes. First, nursing homes are bound by states and federal regulations that require a minimum patient-to-nurse ratio to guarantee patient safety. Surveillance mechanisms such as reporting cards also publish such ratio as an indicator of nursing homes' quality. Nursing homes therefore have the incentive to maintain certain staff-to-patient ratio to guarantee the quality of service. Second, Legal prohibitions and organization challenges also prevent nursing homes from differentiating patient in terms of service quality (e.g. assign much inadequate nursing hours to non-profitable patients) once the patients are admitted into facilities [27]. These two factors imply that besides fixed input such as total number of beds, nursing homes have another care capacity constraint determined by its nurse staff level. Admitting patients that would make total care demand surpass the current staff capacity would incur extra labor cost beyond planned budget. Lastly, as patients differ in their health condition and arrival rate to nursing homes, marginal labor cost incurred by each patient may also differ given their likelihood of triggering extra labor cost.

This paper studies how nursing homes determine admission of patients based on patients' marginal labor cost that is dependent on nursing staff composition that can be decomposed into two parts: formal staff nurses' scheduled hours, and more flexible labor inputs including overtime hours or contract nurses. Facing uncertainty in future patient volume and their health condition, nursing homes typically keep a formal staff level that would not be insufficient during demand peak and rely on more flexible labor inputs that can be assigned on an on-call basis to cope with short-term increase in necessary nursing services. Although using overtime or contract hours incurs higher hourly rate, it is more cost effective in the long run by allowing nursing homes to achieve higher flexibility and save more wage and employee benefit cost ([30], [37]). I examine whether nursing homes become more willing to admit Medicaid patients when their ability to use overtime hours is further limited. Since Medicare patients are mostly discharged from acute care settings and enter nursing homes for recovery purpose, they are more likely to incur usage of overtime hours as they tend to arrive at less predictable rate and require more intensive healthcare during their stay. For example, a new Medicaid patient may only require minor assistance in daily activity and meal preparation that can be planned on a bulk operation basis, whereas an additional Medicare patient may require close monitoring on health status and other professional cares. I introduce more details on nursing staff difference and patient types in section 2.

The impact of nurse staff level on patient composition is difficult to test empirically since resident characteristics and corresponding staffing level are likely to be endogenous. My identification strategy leverages on the states' regulation on health provider's ability to assign mandatory overtime shift to nurses as an exogenous shock to nursing homes' staffing composition in terms of formal nurse staff hours versus contract nurse hours. Starting from 2000, 16 state passed policy restricting the use of mandatory overtime on nurse employees, including typical features such as maximum hours per shift, prohibiting work beyond scheduled shift, and required resting time between before next shift. Table 1 summarizes each state's timing of implementation and legalization details. The regulations prohibiting overtime hours were implemented for the goal of improving quality of care through reducing overtime working which are documented to increase tiredness, job dissatisfaction and medical errors among nurses([11], [41], [45], [32], [5], [43]). However, [37] found that as a strategy to reduce operation cost, nursing homes respond to restrictions on overtime by reducing the staffing level of permanent registered nurses (RNs) and substitute with contact (travel) nurses under situations of unexpected increase in demand (e.g. discharged patient from hospital inpatient treatment). The differential timing of restriction passage across states provides allows me to approach the question in a difference-in-difference (DID) framework. Under the assumption that the trajectory of facilities' outcomes in treated states did not have statistically significant divergence before the passage of regulation (i.e. outcomes show parallel trend in outcomes between treated and control facilities in pre-period), the DID model can identify the impact of prohibiting mandatory overtime on staff level and share of Medicaid patients.

A plausible threat to the assumption of DID model is that the passage of restrictions on mandatory overtime might be targeting some differential trend before the year of intervention. For example, it would bias the DID estimate if states implemented the restriction because prohibiting mandatory overtime can help addressing the nurse supply shortage, which induces decreasing nurse staffing level and patient selection even in the pre-period. To address this concern, I apply a matching algorithm that selects ideal control facilities for each treated facility based on variance of outcome difference during the pre-period. I conduct the matching process for each outcome of interest followed by an event study analysis to verify that the parallel trend assumption required by DID is satisfied in the after-matching sample. The matching algorithm and DID specification are discussed in further detail in section 4.

My analysis is developed in three parts. In the first part, I replicate the analysis in [37] to estimate the impact of regulations on the nurse staffing level measured as RN hours per patient per day. Consistent with [37], I found the RN staffing hours dropped by around 2.7 percent in treated nursing homes following the restriction on mandatory overtime.

In the second part I study whether the decreased staffing level caused change in selective admission behavior. The ideal outcome to identify the selection after regulations would be share of Medicaid residents among newly admitted ones in treated nursing homes. Unfortunately, due to data limitation I use share of Medicaid residents at facility-year level (i.e. residents that have been living in a nursing home before the treated year are captured in the outcome) as a proxy. I found nursing homes in treated states increased share of Medicaid patients by around 1 percentage point on average, consistent with the hypothesis that patient composition is affected by differential marginal labor cost.

I also conduct heterogeneous analysis by baseline share of Medicare patients as a measure for nursing home's specialization in serving Medicare patients. The direction of such heterogeneous impact is ambiguous: facilities with higher concentration of Medicare patients may use more overtime hours before the regulation and therefore more affected by the policy; on the other hand, these facilities may find it necessary to invest more in formal staff level (despite some over-staffing cost) because of the more volatile health conditions of nursing homes patients and thus less affected by the regulation. I found facilities with higher share of Medicare patients has no significant change in total RN hours but slightly higher increase in share of Medicaid patients compared to the overall sample (1.4 percentage point). This suggests the impact of policy on patient composition increases in patient uncertainty. Since Medicare patient's arrival and length of stay are much more uncertain compared to Medicaid patients who usually stay at annual basis, nursing homes with higher concentration of Medicare patient may admit more Medicaid patients as a more stable source of income.

In the third part, I performed supplemental analysis to evaluate the approriateness of my outcome proxy measures and the robustness of my empirical findings. I first estimated the policy's impact on total number of patients at facility level. This practice verifies that the change in RN hours per patient day and the Medicaid patients share are not driven by change in the denominator. Second, I conducted robustness test across matching parameters to examine if my findings are sensitive to the choice of parameter. The results are reported in section 7.

This paper contributes to two threads of literature. First, my findings contribute to the literature on health provider's staffing decision on patient outcomes. [35] found negative relationship between formal registered nurse (RN) staff level and adverse events in nursing homes; [10] examined factor substitution in nursing homes and found that higher nursing staff wages are associated with increased usage of psychoactive drugs (i.e. substituting materials for labor) and reduced care quality based on multiple metrics. [6] documented increasing reliance on contract nurses among nursing homes, which is correlated with more deficiency citation as an indicator of compromised care quality. My paper is closely related to [37], where the authors studied the impact of same policy intervention and found a significant reduction in total staff RN hours and substitution with contract nurse hours in response to the regulations prohibiting mandatory overtime. Consistent with results in [6], the authors found increase in deficiency citations as nursing homes outsourcing work previously practiced by formal staff nurses to contract nurses. My first stage analysis confirmed the change in nursing homes' staffing composition after the mandatory overtime regulation using adjusted matching method that allows more power and avoids inappropriate matched groups, and found slightly smaller magnitude of impact. My second stage analysis on share of Medicaid patients reveals that the staffing level affects not only care quality but also patient composition. Although prohibiting mandatory overtime can compromise care quality as nursing homes use more contract nurses, the policy may benefit Medicaid patients through improved access.

Second, it contributes to the literature that investigates selective admission practice among healthcare providers. The access inequality has been well documented in other healthcare industry as patients' differential payment sources and more complicated reimbursement rules of insurance payers create substantial variation in patient desirability. [15] found that patients with more generous health insurance policies are more likely to be admitted to specialty hospitals (compared to general hospitals) conditional on demographics, distance, and health condition covariates. [19] used survey data among dialysis providers and found that three-quarters of respondents recognize cherry-picking patients as a common practice (answering "sometimes" or "frequently"). In the long-term care setting, [25] and [29] both found that nursing homes are less likely to admit Medicaid patients when occupancy rate is relatively higher. In terms of policy implication, policies with objective to reduce total healthcare expense through capitation payment (e.g. managed care organizations) or relating reimbursement to outcome-based quality metrics can also incentivize providers to select against less profitable patients (e.g. [47], [22]). [25] conducted counterfactual analysis to examine potential policy efforts to reduce selective admission in nursing homes industry. The author found that policies like forcing admission on a "first come, first serve" basis or raising Medicaid reimbursement may improve access for Medicaid patients, but likely at expense of crowing out short-term Medicare patients. On the other hand, policies increasing capacity constraint (number of beds) for nursing homes with excessive demand can increase access to both Medicaid and Medicare patients. My findings demonstrate importance of thinking of patient desirability in terms of both marginal cost and marginal revenue. Targeting usage of overtime as a labor input that are used more heavily in treatment of Medicare patients can be another effective solution that can reduce selective admission among nursing homes as well as improves overall health care quality through reduction in negative consequences induced by overtime working.

2 Backgrounds

Nursing homes are certified by Center of Medicare and Medicaid Services (CMS) to provide a broad range of professional care. This can include short-term care patients discharged from acute care setting and stay at nursing homes for recovery process, and long-term care patients, generally the elderly, seeking different levels of assistance in their daily living activities. In this section I introduce the background of nursing home industry regarding to demand for nursing homes and the labor input choice set that nursing homes can choose from according to the variation in demand. On the demand side I discuss the payment source of nursing homes' patients and the incentive for nursing homes to potentially discriminate against Medicaid patients. I then discuss the skill level and differential responsibility of types of nurses typically hired by nursing homes. Lastly, I explain the potential motivation for nursing homes to use overtime hours and contract nurse hours to substitute for regular staff hours and the state regulations on mandatory overtime.

2.1 Patients with different payment source

Patients in nursing homes have three major sources of payments: 1) Medicare reimbursement; 2) Medicaid reimbursement, and 3) out of pocket payment. Patients covered by Medicare are mostly discharged from acute care facilities to receive rehabilitative and therapy treatments for a certain period, after which patients are either discharged to home are community-based care or stay in the nursing homes for long-term care but no longer pay with Medicare. The nursing home expenses by Medicare enrollees are only reimbursed if they are for physician-certified need related to a recent acute care hospital stay that lasted for more than three days, and the cause of nursing home stay need to be for the same injury/illness that required hospitalization.

The reimbursement rate from Medicare is 100 percent for the first 20 days, then patients need to pay copayment of $185 per day as of 2021 until the 100th day, after which patients need to rely on other copayment sources [12]. The reimbursement from Medicare is adjusted based on patient's health condition and the resource cost of inputs in the local health market. Since most patients covered by Medicare are discharged from acute care settings, they tend to require services that are costly to provide and thus allows nursing homes to extract substantial profit from adjusted reimbursement [25]. However, the payment schedule also means that Medicare patients has much higher turn over rate and uncertainty in their arrival rate compared to other typical long-term care patients. According to the Medicare payment Advisory Commission's 2015 report to Congress, the average length of stay for a Medicare resident in a nursing home is 37 days [39].

Patients that are not eligible for Medicaid or Medicare are reliant on their own out-of-pocket payment. The consumption of private long-term care insurance is uncommon in US [8]. private-paying patients are healthier in general, so the daily charge have less variation within facility compared to ones covered by Medicare patients. The variation in charge within nursing home for this group mainly depends on whether the resident shares room with others. As of 2019, the daily expense for a shared room ranges from $153 to $415, with an average of $245; the daily expense for a private room is $290 per day.

As patients deplete enough private financial resources to qualify for Medicaid, the expense at nursing homes is reimbursed conditional on proven need to long-term care. The condition usually requires patients to demonstrate a need for around-clock skilled nurse service that cannot be replaced with home or community care. Medicaid pay full amount of patient's expense. Unless there's a medical need to a private room in a nursing home, Medicaid only pay for a shared room.

2.2 Incentive to discriminate

Nursing homes may select against Medicaid patients at admission due to multiple mechanisms. First, the revenue from treating Medicaid patients is substantially lower compared to Medicare- or private-paying patients. Since Medicaid covers more than 50 percent of patients in nursing homes across U.S., state Medicaid agencies often have strong bargaining power against nursing homes. Moreover, as a method to reduce budget uncertainty more states have transformed reimbursement system into managed long-term care (MLTC) model, where Medicaid pays a capitation fee to a managed care organization (MCO) for enrollees and nursing homes then receive reimbursement from the MCO for service provided. Nursing homes in states that use MLTC in Medicaid system reportedly experience increased administrative cost from coordination with MCOs to clarify necessary resources needed by patients and bargaining on reimbursement since MCOs have the right to refuse payment on for services that are deemed unnecessary. MCOs may also delay the settled payment for months, which will further have adverse impact on nursing home's financial viability [23].

The second related reason is that reimbursement from Medicaid also has far less adjustment for the actual cost incurred by patients. In states like California, Facilities receive no additional compensation for high-needs patients on days not covered by Medicare, and even Medicare reimbursements may not perfectly insure the facility against heterogeneous care requirements. This means that nursing homes may often not get compensated for taking care of patient of conditions that requires more resources. For example, patients with Alzheimer's disease or illnesses such as kidney failure requires more staff hours compared to others. As of 2021, the Medicaid reimbursement rate for nursing home care is approximately 70 percent of what a private payer pays. According to a joint survey in 2020 conducted by American Healthcare Association (AHCA) and National Center for Assisted Living (NCAL) the reimbursement from Medicaid only covers less than 80 percent of cost incurred by Medicaid patients, and more than half (55 percent) of nursing homes are operating at a loss while 89 percent operating a profit margin of 3 percent or less [2]. Figure 1 from [25] demonstrate the substantial difference in Medicaid's and Medicare's contribution in patient payment sources and actual revenue share in nursing homes. The pie chart on the left shows that more than 65 percent of patient days are covered by Medicaid and only about 17.5 percent patient days are covered by Medicare or patient's out-of-pocket payment. However, the pie chart on the right shows that Medicare reimbursement contributes almost the same fraction revenue as Medicaid reimbursement among nursing homes.

Lastly, nursing homes are unlikely to discriminate among admitted patients by source of payment in terms of offering differential quality of care. From a legal perspective, nursing homes certified to accept Medicaid or Medicare patients are required by the Centers for Medicare Medicaid Services (CMS) to provide equal quality to all patients, regardless of payer type. From behavior and economics perspective, providers also have little incentive to discriminate within facility due to behavioral constructs such as trust, fairness and regret, and certain service activities such as dietary service may achieve economic scales of joint production. [27] found no evidence to reject the hypothesis that service quality within nursing homes is a common good.

2.3 Nurse staffing

Nursing homes typically employ three types of nurses differing in their skill level: registered nurses (RNs), licensed practical nurses (LPNs), and certified nurse assistants (CNAs). RNs are federally licensed nurses that receive 2-years training with associate degree or 4-years training with bachelor's degree. The main responsibility of RNs includes recording patient histories, monitoring patient vitals, performing various diagnosis tests, and medication administration. RNs also collaborate with physicians in development of care plans and supervise LPNs and CNAs' job performance [35]. LPNs typically hold one-year training degree and have some responsibility overlap with RNs and CNAs but work under supervision of RNs. Duties often include monitoring patient vitals, handling basic healthcare tasks, and assist patients in their daily activities. CNAs receive 4 to 12 weeks of training and are mainly responsible for assisting patients with basic life activities such as bathing, dressing, eating, toileting [9].

When choosing nursing staff level, nursing homes face a challenge of maintaining a delicate balance between overstaffing and understaffing, which is complicated by uncertainty in staffing needs that comes from two sources: 1) uncertainty in future patient volume and 2) variation in amount of necessary acute care depending on arrival of new patient discharged from hospitals or other acute care settings and sudden changes in the current elderly patient's health conditions. As a common practice to cope with these uncertainties in a cost-effective way, nursing homes typically choose a nursing staff level that will not be sufficient for full capacity scenario (i.e. all beds are occupied) and rely on overtime or contract nurse hour during demand peak, which allows nursing homes to reduce overall labor cost while maintains an ideal flexibility.

Overtime hours refers to hours that are worked by a nurse that exceed their normal weekly scheduled working hours. Full-time for nurses is usually 36-40 hours per week, and hours above this range is considered "overtime.". The overtime shifts can be taken voluntarily by nurses or mandatorily assigned by management team of nursing homes. Without regulations on mandatory overtime, nurses are required to accept overtime shifts and their only option to avoid working overtime is to quit the job [4]. Most nursing homes will offer time-and-a-half or double-time pay for overtime or holiday hours. Despite the higher hourly cost, overtime hours are still cost-effective from perspective of nursing homes for two reasons. First, it helps nursing homes to gain more flexibility because overtime can be scheduled on a short notice, whereas hiring additional permanent takes a substantial lead time. Second, hiring more formal nurses often requires substantial financial commitment due to factors such as union contracts or government labor regulations. Therefore, frequent adjustment of formal staff level is not cost-effective for addressing weekly or daily fluctuations in staffing needs. In addition, nursing homes may delay the due compensation for overtime hours on purpose, which means the actual hourly cost of using overtime may be way below one half of hourly cost for regular hours. For example, multiple nursing homes were involved in lawsuits during 2019 and 2020 for owing unpaid overtime hours of nurse employees, and each were required to pay over $ 200k compensation (e.g. [33], [7], [16]).

In addition to overtime hours, nursing homes also use contract nurses (or agency nurses) to fill short-term nursing shortages. This approach brings similar advantages as using overtime hours as contract nurses can be scheduled on an on-call basis. The per-diem mark up of contract nurse's hourly cost range from 1.25 to 2 times of scheduled formal staff hours ([36], [28]).

2.4 Mandatory overtime regulation

Over the past decade, various studies in the past literature associated overtime of nurses with fatigue and job dissatisfaction among nurses, and consequent medication errors and nurse injuries. [41] found positive relationship between nurse's overtime hours and risk of making medication errors. [46] found that excessive use of overtime increased nurse musculoskeletal problems. Nurses working more hours were found on average to be more fatigued, have more health complaints, and be less satisfied ([13], [32], [43]).

To address the concern over negative impact on healthcare quality and job dissatisfaction caused by overtime, 15 have states passed regulations restricting the use of mandatory overtime for nurses since 2001 [4]. Although the details of the regulations may vary at state level, the mandatory overtime laws prohibit health care facilities from requiring employees to work more than their regularly scheduled hours except during a health care disaster that increases the need for health care personnel unexpectedly. Nursing homes are not allowed to schedule a shift that exceeds 12-16 hours, and nurses are required to have 6-8 resting hours between consecutive shifts (depending on policy details at state level). Also, nurses have the right to refuse overtime working without concern about retaliation from employers ([4], [37]).

Although proponents of policy restricting nurses' mandatory overtime argue that it is beneficial for both healthcare quality and nurses' working environment, past literature evaluation the regulations found contradictory evidence of their impact. [4] examined 2004 National Sample Survey of Registered Nurses and found that Nurses working in states regulating mandatory overtime reported lower levels of mandatory overtime hours than states without regulations or states restricting total work hours. The percent of RNs working 61 hours and over per week in states without regulations was lower than that in states with regulations. However, the regulations do not prohibit nurses from taking overtime shifts voluntarily. This allows nurses to earn extra compensation at their willing for, but also leaves gaming room for nursing homes. In the survey data used by [4], 62% of RNs answered reported being pursued to take "voluntary" overtime shifts. Therefore, the regulations can most likely decrease nursing home's ability to use overtime hours at intensive margin instead of extensive margin. Moreover, the restriction on mandatory overtime does not necessarily induce nursing homes to increase formal nurse staff level (i.e. use more schedule hours) as the uncertainties on patient side remain. [37] found that in states that prohibit mandatory overtime of nurses, nursing homes use fewer total hours from formal RN staff nurses (i.e. sum of schedule hours and overtime hours from formal staff RN) and substitute the reduced use of overtime with contract nurses. The authors also found that the number of deficiency citations increased in states with restriction on overtime, which could be caused by reduction in total service hours or quality reduction associated with use of contract nurses.

3 Conceptual Framework

In this section I introduce a model that intuitively explains the expected impact of regulation that prohibits usage of mandatory overtime hours (for convenience, I refer to the policy as "overtime regulation" in the rest of this paper) to on nursing homes' staff and patient admission decision. I begin with a modified set up connecting the model in [25] that describes nursing homes' selective admission behavior and the model in [37] that describes nursing homes' staffing decision process based on a two-stage cost minimization problem. Lastly, I conduct comparative statistics analysis that derives predicted overtime regulation's impact on patient composition in treated nursing homes.

Consider a nursing home j that fixed total beds b_j. The nursing home expects future patient i whose type is drawn from three payment types: $\theta_i \in \{\theta_{Mcare}, \theta_{Mcaid}, \theta_{private}\}$. Prospective patients arrive according to a Poisson process with rate parameter λs. To allow for heterogeneous prospective patients pool, the arrival rates of patient types differ across nursing homes, i.e. $\lambda \in \{\lambda^j_{Mcare}, \lambda^j_{Mcaid}, \lambda^j_{private}\}$. For the sake of convenience, I refer to the set of patient arrival rate $\{\lambda_\theta\}^j$.

A typical nursing home facility uses three different staffing hours of work by registered nurses (RNs): formal staff's scheduled hours, formal staff's overtime hours, and contract nurse's staffing hours. As mentioned above, formal staff level and the corresponding scheduled hours are assumed to be fixed in the medium or long term (i.e. quarterly or yearly), while overtime hours and contract hours are relatively more flexible labor for nursing homes to cope with shortage in staff level in the short run. Let R_j, O_j, C_j denote facility j's regular scheduled hours, overtime hours, and contract hours, respectively. The total hours staffing hours is then the combination of three types of hours: $S_j = R_j + O_j + C_j$. Let w_R, w_O, and w_C denote the hourly cost of three types of hours. According to the industry facts discussed in section 2, I assume that $w_R < w_O \leq w_C$. Intuitively, nursing homes can only expect to use overtime hours up to a fraction ν of scheduled hours, due to the physical constrain of nurses and other factors such as labor union contest or local regulations. Therefore, the overtime hours can be modeled as $O_j = \nu R_j$, and we can denote the total hours from formal RNs as $\tilde{R_j} = (1 + \nu)R_j$

Let B_j denote the total number of beds of the facility, N_j denote the number of patients. The facility's enrollment level is then $E = min\{N_j, B_j\}$, and $\frac{S_j}{N_j}$ reflects nursing home's staff-to-resident ratio. x_j denote the random patient's demand for health care provided by nursing staff, which is determined by number of patients in the facility as well as patients' health conditions. I assume x_j follows a continuous distribution $F(x)$ with density $f(x)$. Moreover, nursing homes need to maintain a minimum staff-to-ratio l assumed to be fixed in the short run, as the ratio is generally determined by external factors such as policy regulations and market competition [30]. In addition, we can define the facility's formal staff care capacity as $\eta_j = \frac{(1+\nu)R_j}{l}$, which measures the maximum number of patients that can be taken care of by formal staff RNs.

3.1 Staffing Level Decision

Given the set up above, nursing home's choice of staff level within a time interval can be described in a two-step cost minimization problem. In the first stage, nursing homes decided a formal staff level and scheduled hours with an imperfect prediction of the future needed staff hours; in the second stage, after observing the actual necessary staff hours, the nursing home chooses overtime and contract nurse hours that minimizes total labor cost subject to the fixed minimum staff-to-nurse ratio. Mathematically, the set up can be written as:

$$\min_{R_j \geq 0} W_j^* = min\{w_R R_j + E[Z(R_j, x)|\{\lambda_\theta^j\}]\}, \tag{1}$$

where W_j^* is the minimized total nursing labor cost, and $E[Z(R, x)|\{\lambda^j\}]$ is the expectation of the total cost of overtime and contract hours conditional on j's set of patients arrival rate discussed in section 3.2, which can be written as:

$$\begin{aligned} Z(R, x) = & \min_{O_j \geq 0, C_j \geq 0} \{W_O O_j + W_c C_j\} \\ & s.t. \;\; S/E \geq l, \\ & O_j \geq \nu R_j \end{aligned} \tag{2}$$

3.2 Patient Admission

Following [25], each patient instantaneously applies for admission at the facility upon arrival, and the facility instantaneously chooses whether to admit the patient. If a patient arrives when the facility is full, the patient is automatically rejected. If admitted at time t, the patient generates marginal profit π_i that can be decomposed into marginal revenue and marginal cost when the facility admits the patient:

$$\pi_{it} = MR_{it}(\theta_i, h_{it}) - MC_{it}(N_{j,t}, h_{it}, \eta_j), \tag{3}$$

where h_{it} is the patient's health status at time t, $N_{j,t}$ is facility's number of patients at $t-1$, and η_j is the facility's short-term formal staff care capacity defined in section 3.1. I further assume that the marginal cost decreases in formal staff care capacity θ_j and this effect is stronger for patients with worse health condition, i.e.

$$\frac{\partial MC_{it}(N_{j,t}, h_{it}, \eta_j)}{\partial \eta_j} < 0; \qquad \frac{\partial MC_{it}(N_{j,t}, h_{it}, \eta_j)}{\partial \eta_j \partial h_{it}} > 0 \tag{4}$$

The first term in equation (3) reflects the fact that the facility receives higher revenue if the patient's payment source is Medicare and can expect higher adjusted reimbursement from Medicare (or Medicaid, dependent on state policy) if the patient's health status is relatively worse. Therefore, the first term is higher for Medicare patients and decreases in h_{it}. The second term increases in $N_{j,t}$ and decreases in R_j and h_{it}. The intuition is that the marginal cost incurred by patient i is determined by the patient's health status at admission and whether the facility would incur additional labor cost (i.e. initiate usage of overtime hours or contract nurses) if admit the patient. For example, if the baseline patient level $N_{j,t}$ is sufficiently high for the maximum scheduled hours allowed by facility's formal staff care capacity (η_j), the marginal cost of admitting a patient that mainly seeks normal long-term care (e.g. daily medication, assistance in daily activities) can be lower than admitting a patient that enters for recovery purpose (e.g. from an acute care surgery) and requires intensive nursing services. Given the general pattern that Medicare patients tend to be of worse health condition compared to Medicaid patients, equation (3) implies that the marginal revenue generated by Medicare patients are not necessarily higher than Medicaid patients.

For a time interval $t \in [\,\underline{t}, \bar{t}\,]$, assume that the facility determines a formal staff capacity $\eta_{j\underline{t}} \geq 0$ at the beginning of the period with imperfect prediction of the patient volume and health condition in the time interval. Consistent with the common practice with nursing homes industry, the formal staff level is assumed to be fixed commitment within the period as most nursing homes adjust their formal staff level at quarterly or yearly basis [37]. When determining admission of patients, the facility chooses an admission plan that is a set of profit lower bound at each time τ, $\{\underline{\pi}_t\}$, such that a patient arriving at time τ is admitted if and only if:

$$\pi_{it} \geq \underline{\pi}_t. \tag{5}$$

At each time t, the chosen profit lower bound maximizes present discounted value of future admitted patient profits, conditional on the known arrival rates of types of patients:

$$E[\sum_{\{\tau_i^a \geq t, N_{\tau_i^a} < b, \pi_i \geq \pi_{\tau_i^a}\}} exp(\rho(\tau_i^a - t))\pi_{i\tau_i^a} | \{\lambda^j\}], \tag{6}$$

where ρ is the discount rate, and τ_i^a is the arrival timing for patient i that arrives after t. According to the Poisson process assumption the patient arrivals are memoryless process. And since the facility cannot predict future patients within short run and residents are indistinguishable after admission, the facility need only condition its policy on its current patient level and formal staff level. Therefore, equation (5) and (6) can be combined and rewritten as:

$$\pi_{it} \geq \underline{\pi}_t(N_{t-1}, \eta_{j\underline{t}}, \{\lambda_j\}) \tag{7}$$

3.3 Impact of Prohibiting Mandatory Overtime

I now discuss the impact of mandatory overtime regulation from the above set up. I first summarize hypothesized impact on nursing staff composition in [37], and then move on to derive the regulation's impact on patient composition.

As discussed in section 2.4, since states' regulations did not prohibit voluntary overtime hour, the nursing home's ability to use overtime is more likely to decrease at intensive margin rather than extensive margin. The regulation can therefore be modeled as a decrease in ν, which measures the upper bound that a nursing home could assign overtime hours as a fraction of scheduled hours.

Using backward induction to solve the set up in section 3.1, [37] derived two hypothesis on nursing home's staffing composition after the mandatory overtime regulation. First, for nursing homes that have low initial staff capacity of formal staff RNs (i.e. η_j), prohibiting the mandatory overtime (i.e. $\nu \downarrow$) would decrease the optimal formal staff hours and increase the contract hours (i.e. $\tilde{R}_j \downarrow$, $C_j \uparrow$). The intuition is that facilities with low initial formal RNs capacity may face more uncertainty in the patients demand and are thus more reliant on flexible resources, i.e. overtime hours and contract nurses. Second, for nursing homes that have high initial formal RNs capacity, the total staffing hours of formal RNs may still decrease after the regulation if the $w_C - w_O$ is sufficiently small. The authors conducted simulation test for the above predictions and confirmed that the predictions hold for $w_C \in [w_O, \frac{4}{3}w_O]$, which is consistent with general industry pattern. The authors empirically tested the regulation's impact on total formal RN hours and found that facilities in treated states reduced total formal staff hours by 3.9% on average. Due to data limitation, the authors were only able to test usage of contract hours using cross sectional data in 2012 (i.e. after all treated states have implementation) in a geographical regression discontinuity framework. The authors find nursing homes in treated states has small but statistically significant increase in usage of contract hours.

The reduction in care capacity caused by mandatory overtime regulation thus decreases $\eta_{j\underline{t}}$ in equation 6. Equation 4 implies that as the formal staff's care capacity decreases, the marginal labor cost for treating Medicare patients increases more than Medicaid patients because Medicare patients are generally of worse health condition and enter nursing homes for recovery purposes. Therefore, we can expect the share of Medicaid patients to increase in treated nursing homes as the profit premium for treating Medicare patients following the regulation.

4 Research Design

In this section I discuss the structure of my analysis and the empirical framework I used to identify the impact of regulations prohibiting mandatory overtime. My analysis follows 3 steps. In the first step, I replicate the analysis in [37] to estimate the impact of policy intervention on staffing composition of nursing homes. I study the average impact on total staff RN hours per patient day as a proxy for usage of contract nurses, which is the sum of scheduled hours and overtime hours worked by nursing home's formal nurse staff divided by number of patient days. Since nursing homes were only required to report their usage of contract nurses after 2009, I have no direct measure of trend in usage contract nurses. My analysis's focus on estimating the change in RN hours among all three types of nurses is motivated by two factors. First, RNs are affected by all state-level regulations on mandatory overtime because the overtime pattern is most prevalent among RNs. For example, CNAs are excluded from the overtime regulations in New York and some other treated states ([37]. Second, as introduced in the section 2, RNs possess the highest skill level among nurses employed by nursing homes and are mostly likely to be used in treating Medicare patients since they are of relatively of worse health condition when arrive at nursing homes ([9]).

In the second step, I estimate the mandatory overtime regulation's impact on patient composition in terms of payment sources. I use two measures to proxy for the patient composition. First, I estimate the change in share of patients paying with Medicaid for each nursing homes in each calendar year. Second, I estimate the change in total number of patients for each nursing homes at the same scale, which is informative about whether the change in patient composition is driven by reduction in overall service capability or substitution between types of patients due to the differential marginal labor cost.

Lastly, I conduct a heterogeneity analysis to explore whether the regulations have more or less impact on nursing homes that are more specialized in treating Medicare patients, which is defined using baseline share of Medicare patients at nursing homes.

4.1 Identification Strategy

The differential implementation timing of states' regulations on mandatory overtime presents a quasi-experimental environment and the regulations' impact can be estimated in a difference-in-difference framework. However, a key challenge in identifying the impact of prohibiting mandatory overtime hours is that states' decisions to implement this policy intervention are most likely to be associated with other factors that can affect nursing homes' staffing and patient composition in other channels. This endogeneity of treatment policy can bias my estimate because the estimated impact of regulations may pick up contemporaneous change in the interested outcome that are not caused by the policy. For example, states that have higher shares of nurses enrolled in labor union may face more pressure to pass the regulation compared to other control states, but such difference in labor union coverage may also cause divergence in trajectory of nursing homes' staffing and patient composition in other ways such as higher bargaining power in wage negotiation. Therefore, estimates using the difference-in-difference requires parallel trends of interested outcome between treated group and control group.

To estimate the impact of regulations in presence of concern over policy endogeneity, I start with an event-study analysis that can both verify that the matched sample has no pre-trends in total RN hours per patient day or share of Medicaid patients prior to the passage of mandatory overtime regulations and estimate the dynamic impact of the regulations. The specification can be written as:

$$Y_{icst} = \sum_{\tau \in [-5,-2] \cup [0,5]} \sigma_\tau D_\tau \times Treated_i + \sum_{\tau \in [-5,-2] \cup [0,5]} \kappa_\tau D_\tau + \ \delta_1 X_{ct} + \delta_2 X_{st} + \eta_i + \gamma_t + \epsilon_{icst}, \tag{8}$$

where Y_{icst} refers to the interested outcome for facility i in county c state s and in year t. D_τ an event year indicator that equals 1 if the focal year is τ years from the treatment year. For example, for nursing homes in New York that implemented regulation in 2009, D_{-1} equals 1 for calendar year 2008 and D_1 equals 1 for calendar year 2010. The parameters of interest are σ_τ, which identify the divergence in pre-period outcome trends between treated and control units for $\tau \leq -2$, and the regulation's dynamic effect for $\tau \geq 0$. The event year dummies are included in equation (1) as event year fixed effects to control for unobserved factors in a particular event year that are common to both treated and control group and may have impact on outcome of interest. η_i is facility fixed effect that controls for time-invariant unobservables associated with treatment status and outcome of interest. γ_t is calendar year fixed effect that controls for unobserved macro factors in a particular year that affect both treated and control facilities.

X_{ct} controls for county level observable characteristics, including: 1) demographics characteristics — log of population, share of population that are aged over 60, share of black population; 2) economics features — income per capita, poverty rate, and rural status; 3) local health resource — number of hospital beds for every 1000 individuals aged over 60, and Medicare managed care penetration rate (i.e. share of Medicare population that are covered by a managed care plan, which lowers the expected payment that can be received for nursing homes). X_{st} controls for two state level policies that may affect nursing home's incentive to select against Medicaid patients. The first policy is Medicaid Bedhold policy, nursing homes are required to keep a Medicaid patient's bed during his short-term leave for therapeutic purpose or family visit. Medicaid may compensate the nursing homes for a certain amount depending on state level details. The second policy is Medicaid CaseMix, which is similar to Medicare's Inpatient Prospective Payment Systems (IPPS), where patients are classified into Resource Utilization Groups (RUGs) according to their estimated required amount of daily care, and state Medicaid program will reimburse nursing homes for treating patient based on the RUG group of the patient.

After ensuring the validity of parallel trends assumption in my analysis sample, I proceed to estimate the average causal impact of prohibiting mandatory overtime on RN staff hours and share of Medicaid patients in nursing homes in a difference-in-difference framework. To test for the robustness of my estimated impact regarding covariates, I start with only facility and calendar year fixed effects and gradually add in the sets of county and state level covariates introduced in equation (12). My preferred full specification for interpretation of estimates can be written as:

$$Y_{icst} = \beta_0 + \beta_1 regulation_{icst} + \beta_2 X_{ct} + \beta_3 X_{st} + \eta_i + \gamma_t + \epsilon_{icst}, \tag{9}$$

where $regulation_{st}$ is an indicator variable that equals 1 if the facility i is in a state that implemented mandatory overtime regulation before or in calendar year t. The parameter of interest is β_1, which identifies the average treatment impact from prohibiting on mandatory overtime across years after the policy timing.

4.2 Matching Algorithm

To further control for impact from unobservable covariates that cannot be absorbed by fixed effects in equation (1), I employ a matching algorithm to select the most appropriate control units for each facility in treated states. In particular, the algorithm is processed in three steps. In the first step, for each treated facility i in a state that implemented mandatory overtime regulation in year t_0, I use all facilities in the control group as donor pool and calculate the arithmetic outcome distance between the focal treated facility i and control candidate j for years in the pre-period:

$$D_{ijt} = y_{it} - y_{jt} \quad \forall\ t \leq T; i \in \{treated\}, j \in \{never\ treated\} \tag{10}$$

In the second step, I compute the variance of distance values before treatment year t_0 as

$$V_{ij} = Var(D_{ijt}) \tag{11}$$

Lastly, the control unit j included in the analysis sample if $V_{ij} \leq k$, where k is the threshold parameter that can be adjusted. I am using rule of thumb to set k equal to $\frac{1}{100}$ of standard deviation of the interested outcome in the whole unmatched sample.

Since the policy intervention in this paper took place at differential timing across treated states, a potential challenge in this setting for difference-in-difference framework is that overtime regulation's impact may vary over time. For example, nursing homes may increase usage of contract nurses in the short term because of the long lead time to hire new formal staff nurses, but gradually increase their formal staff level if this is more cost-effective in the long-term. As well illustrated in recent literature (e.g. [26], [18], [17]), this dynamic treatment effect could bias the estimates if units that are treated prior are used as control group to be compared with units that are treated in later periods. In this case, the control group's post-treatment outcome trend is no longer an appropriate counterfactual for treated group's outcome trend as the control group's outcome will differ on its own even in absence of policy intervention among treated group. I therefore I restricted the donor pool to only facilities in states that never implemented overtime regulation in my study period to avoid bias caused by dynamic treatment effect.

After matching qualified control facilities to each facility in the treated group, I proceed to pool the comparison groups together and drop duplicated observations. This matching process is conducted for each outcome of interest, so my analysis sample may vary across study outcomes. I conducted robustness check to test the stability of my estimation across other values of k, which I will discuss in detail in the robustness check section. The intuition behind this algorithm is that if there's no statistically significant divergence in the pre-period outcome trends between treated facility i and control facility j (i.e. the parallel trends assumption holds), the variance of outcome distance between the two facilities should be sufficiently small. This matching method is similar to the k-nearest-neighbor subset algorithm that is widely discussed in machine learning literature and economic papers using difference-in-difference framework (e.g. [31], [37], [3], [24]). The algorithm used in this paper differ from the k-nearest-neighbor algorithm in that instead of forcing the number of control units to be k for each treated unit, my matching process is based on a variance threshold and thus allow to number of matched control units to differ across treated units. For example, some facilities may have 100 matched donors that satisfy the variance threshold, whereas some treated facilities are dropped from analysis sample because it does not have any control facilities in the donor pool. This approach generates more power by including more control units, while avoids using inappropriate comparison where there is significant trend divergence between treated unit and the matched control units, even if the control unit is determined as nearest neighbor.

Compared to other matching methods to determine control group such as propensity score matching based on observable covariates, the algorithm matching on pre-period outcome trends is more appropriate due to my data limitation on facility level covariates. Without sufficiently large set of observable covariates, the performance of propensity score matching would be compromised as the control group may still differ from treated group in many unobserved dimensions [44]. Moreover, compared to synthetic control approach commonly used to supplement difference-in-difference analysis (e.g. [1], [20], [42]), my matching approach generates much less bias from overfitting issue which is a common concern when making prediction with small sample size and high dimensional data. Since my unit of analysis is at facility level, the overfitting bias is most likely to happen as earliest event years in my study data ranges from -9 to -5 yet the size of donor pool is over 10,000, which means the synthetic control method would perform the prediction task on a 5 by 10,000 sample or even larger.

5 Data Sample

In this section I discuss the data sources and sample restriction process used to generate my analysis sample. The data sample I use comes from three sources. I use publicly available data from LTCFocus project for outcome measures including RN hours per patient per day, share of Medicaid patients. For heterogeneity analysis I also use share of Medicare patients, as well as total beds at facility level to construct baseline HHI at county level. LTCFocus.org is a product of the Shaping Long-Term Care in America Project being conducted at the Brown University Center for Gerontology and Healthcare Research and supported in part by the National Institute on Aging. The project makes public version of administrative datasets including Online Survey Certification and Reporting (OSCAR) and Minimum Data Set (MDS). Both these administrative datasets contain detailed information on nursing home characteristics including staffing and equipment level and patient characteristics for each admission. The LTCFocus then makes these data publicly available by aggregating the data at facility level for each survey year, which include facilities in all U.S. states except Alaska.

I also used Area Resource Files complied by LTCFocus for information on local long-term care resources that are included in the control county covariates mentioned in specification section. I collect data on county level demographic covariates from The Surveillance, Epidemiology, and End Results (SEER) Program for share of senior population and share of black population, and economic statistics from Bureau of Economics Analysis (BEA) for income per capita. Lastly, I use 2013 Rural-Urban Continuum Codes to construct a new simpler categorical variable defining rural status of counties based on access to urban healthcare resources. Rather than counties that are defined as a metropolitan area regardless of population, and counties defined as nonmetropolitan urban population of 2500 to 20,000 are assigned value 1 to generalize the easier access to health care resources in urban area. Counties defined as nonmetropolitan urban population of 2,500 to 20,000 population and nonadjacent to metropolitan area are assigned value 2. Counties defined as completely rural, or less than 2,500 population are assigned value 3 regardless adjacent to metropolitan area.

The available data expands from 2000 to 2017 with total of 18,218 unique facilities and 16 treated states from 2001 to 2012. Since both the parallel pre-trend assumption of difference-in-difference specification and the matching algorithm using pre-period outcomes requires a long enough pre-period, I excluded facilities in states that passed mandatory overtime regulation before 2005 (including California, Maine, Minnesota, Maryland, Washington, and West Virginia). Also, the Affordable Care Act (ACA) passed on 2012 promoting quality care encouraged further collaboration between skilled nurse facilities and hospitals, which induce an increase in patients discharged from hospitals and covered by Medicare for their first 100 stays in SNFs. Although the Massachusetts is last state that passed the policy in 2012, my estimate on patient composition might still be biased by the dynamic impact on patient composition in nursing homes from the impact driven by ACA's quality care reform. I therefore exclude Massachusetts in the sample and limit study period to 2013 (most ACA quality care provisions phased in in after 2013). I then limit the sample to facilities that have no missing observation between 2000 and 2013. The whole sample restriction process leaves the unmatched sample with 8 treated states with 3644 unique facilities, and 34 control states with 8461 unique facilities in the unmatched whole sample.

Figure 2 shows the time trend of average outcome of interest by ever treated facilities and never treated facilities. Panel A plots average RN hours per patient day across calendar years. The two groups have almost parallel trend of RN hours, with minor divergence in 2005, 2006 and 2008. The sharp increase in RN hours since 2008 reflects the impact of the Great Recession on nursing home industry. Past literature documented mixed evidence on nursing homes' change in demand for RNs during the recession, but reached consensus that patients demand substantially decreased because the large-scale unemployment increase made families switch from formal long-term care (e.g. nursing homes) to informal long-term care from unemployed family members (e.g. [21], [34], [40]). Figure 3 shows the annual trend of average total number of patients across all facilities in the unmatched whole sample. The number of patients dropped substantially since 2008. By construction of the variable RN hours per patient day discussed in section 4.1, the sharp trend break in panel A is more likely to be driven by the decrease in nursing homes' number of patients as the denominator.

Panel B plots the annual trend of facility level Medicaid patients share by ever treated and never treated group. Both groups exhibit a downward trend of share of Medicaid patients, suggesting presence of general patient selection pattern against Medicaid patients. While the trend for ever treated group becomes flatter compared to never treated group since the starting of state overtime regulations in 2005, the figure shows salient trend divergence between the two groups in pre-periods (e.g. 2001 to 2004, and 2008 to 2009) that may bias the estimates from the whole sample using difference-in-difference framework. I thus conduct event study analysis using whole sample restricted to only treated facilities to test for any significant pre-trend in RN hours and Medicaid patients share among treated facilities. The specification can be written as:

$$Y_{icst} = \sum_{\tau \in [-5,-2] \cup [0,5]} \sigma_\tau D_\tau + + \delta_1 X_{ct} + \delta_2 X_{st} + \eta_i + \gamma_t + \epsilon_{ict}, \tag{12}$$

where the indicator for treated states in equation (12) is removed as this practice only include facilities in treated states. Figure 5 reports estimated leads and lags, where panel A reports analysis on RN hours per patient day and panel B reports Medicaid patients share. The figure illustrates that facilities in treated states have significant change in both staffing level and patient composition before the overtime regulation. Matching algorithm is thus necessary to better control for potential estimation bias from unobservable factors.

As mentioned in the method section, I applied the matching method each time for analysis on different outcomes. Since the matching algorithm selects control facilities that have variance of outcome distance relative to the focal facility below a certain threshold, the analysis samples may further differ by outcome of interest as treated facilities with no eligible matched control facilities are left out in the matched sample. Table 2 summarizes facility, county, and state level observable characteristics across unmatched whole sample and analysis samples for RN hours and Medicaid patient share. The matching process for RN hours uses parameter $k = 0.005$ and drops 324 treated facilities and 357 never treated facilities. The after-matching method for Medicaid patients share uses $k = 4$ and drops more facilities (1138 treated and 1472 untreated), which reflects the more substantial pre-trends as indicated in figure 2 panel B. The observable characteristics are fairly balanced across samples, which suggest the matching process does not incur strong compromise on external validity through sample selection.

As discussed in section 4 when motivating heterogeneity analysis by baseline Medicare patients share, nursing homes may have large variation in targeting patient types and correlated characteristics. Figure 4 shows the distribution of nursing homes with different levels of Medicare patient share as of 2004, the latest year when all states remain untreated in my unmatched sample. The vertical red line marks the third quantile of the share distribution. As of 2004, 75 percent of nursing homes have around 15 percent of Medicare patients out of all patients within facility, and the other 25 percent of nursing homes have Medicare patients share ranging from 15 percent all the way to 100 percent. The figure suggests there's large degree of variation in nursing home's operation strategy in terms of patient specialization, which may lead to heterogeneous impact from overtime regulation. Table 3 summarizes the average characteristics in 2004 by third quantile of Medicare patients share in 2004. The two subgroups have substantial difference in many dimensions. Facilities that are more specialized in Medicare patients tend to have higher RN staff level and located in counties with larger population size and higher income. The higher RN staff level correspond to my previous notion that Medicare patients in nursing homes require more intensive care due to their worse health condition compared to Medicaid patients.

6 Empirical Findings

6.1 Total formal RN hours

In this section, I examine the mandatory overtime regulation's impact on nursing home's formal staff level measured by staff RN hours per patient day (RN HRPD) using the after-matching sample. I first report event study coefficients from equation 12 to show that there is no statistically significant trend divergence in the after-matching sample between treated and control group before the implementation of mandatory overtime regulation. Second, I report the regression results from equation 9 to show that nursing homes in treated states significantly reduced usage of formal staff RN hours after the regulation. I also report findings on heterogeneous treatment impact by baseline share of Medicare patients as a proxy for nursing home's specialization in treating Medicare patients. The results indicate that most of regulation's impact is driven by nursing homes that are less specialized in treating Medicare patients. These results establishes the first stage of my identification strategy, and confirms the exogenous change in staffing composition that I rely on to identify the effect of lower usage of overtime hours in increasing share of Medicaid patients.

Figure 6 plots leads and lags of intersection term coefficients σ_τ from equation 12, where the vertical line marks one year before the regulation on mandatory overtime was implemented in the treated state. I restrict the study period from event year -5 to 4 in order to perform the analysis on a balanced panel. For states that implemented the policy in 2009 (i.e. New York, New Jersey and Texas), the maximum event year is 4; for states that implemented the policy in 2005 (i.e. Illinois and Connecticut), the minimum event year is -5. The figure confirms the absence of pre-trend divergence that would bias the estimated treatment effect. The post periods coefficients indicate an immediate decrease in total RN staff hours following the regulation, and the negative impact lasted for the following event years. The staff reduction became less salient in the following one or two year as coefficients became negative but non-significant, but gradually recovered as both magnitude and significance exhibit increasing trend increase from first to forth event years.

Table 4 reports the estimated regulations impact on staff RN hour from the difference-in-difference model specified in equation (9). I estimated the impact using sample matched on whole sample as well as samples matched on nursing homes with above/below third quantile of baseline share of Medicare patients. Since facilities with higher baseline share of Medicare patients could be specialized in treating Medicare patients, I expect the regulation to have less impact on them because these facilities may have higher staff level at the baseline because of higher healthcare demand from Medicare patients, or the facilities' better prediction of future patient volume.

Column 1 to column 3 shows estimated β_1. For convenience of interpretation, I replace the dependent variable from absolute level of staff RNs HRPD to its logarithm to have better reflect the magnitude of average treatment effect. Column 1 starts with only county and calendar year fixed effect. The estimated coefficient indicates significant reduction in total RN staff hours by 4 percent among nursing homes in treated states following the regulations prohibiting mandatory overtime. Column 2 and column 3 add in county level covariates and state level policy covariates discussed in section 4.1, to verify that the estimated impact is not sensitive to controlling for other covariates that may affect nursing home's staff level decision. Column 3 reflects the estimation result from full specification in equation (9) and is my preferred one for interpretation. The coefficient in column 3 indicates that nursing homes in treated states decreased total formal RN hours by 2.7 percent on average, and the reduction is statistically significant with p value less than 0.01. My estimated treatment effect is in the same direction but of smaller magnitude compared to the impact found in [37], potentially due to the difference in matching mechanism discussed in section 4.2.

Column 4 to column 9 explores the heterogeneous treatment effect across nursing home's extent of specialization in Medicare patients. I also performed event study on the two after-matching samples respectively to confirm the validity of parallel trend assumption for both subgroups. The results are reported in appendix figure A.1. Nursing homes with baseline share of Medicare patients above third quantile (column 4 to 6) are less affected by the mandatory overtime regulation. Estimated coefficients are close to 0 and not statistically significant. Nursing homes that have less baseline share of Medicare patients (column 7 to 9) exhibit negative change in total formal RN staff hours that are statistically significant and of larger magnitude compared to column 1 to 3 (4.6 percent).

6.2 Share of Medicaid patients

Following the first stage impact in staffing composition caused by mandatory overtime regulation, I move on to explore the change in patient composition caused by reduction in total staff RN hours. I estimate the share of Medicaid patients at facility level measured in percentage points. As discussed in section 3.3, total RN staff hours decreased after the policy intervention, and nursing homes in treated states would become more reliant on contract hours as a flexible labor input. Since Medicare patients are more likely to incur overtime or contract hours as their health condition requires more professional care and their arrival rate are less predictable, I therefore expect share of Medicaid patients would increase in treated facilities.

Figure 7 estimated lead and lag intersection terms in the event study specified in equation (12). Figure 7 shows no significant pre-trend in the after-matching sample, suggesting that there are other state level unobservable factors that affect both nursing home's overtime usage (which in turn induces the regulations prohibiting mandatory overtime) as well as the patient composition in nursing homes in the unmatched data. The coefficients for event years after treatment implies a dynamic treatment pattern. Coefficients for event year 0 to 2 are positive but not statistically significant, and coefficients for event year 3 to 5 shows gradually increasing magnitude and are significantly positive. Since the sample is balanced up to event year 4, this increasing pattern is not driven by sample selection issue. Instead, the dynamic estimated impact could be driven by the fact that my dependent variable measures the share of Medicaid patients at the annual survey date, i.e it captures the existing patients that were admitted before the survey year and stay in the facility for long-term. The larger impact in later event years could thus reflect the change in types of newly admitted patients shortly after the policy intervention.

Table 5 reports estimated mandatory overtime regulation's average impact on share of Medicaid patients. Column 1 to 3 present the estimations from whole matched sample, where each column has the same corresponding specification as in table 4. Nursing homes in treated states on average increased share of Medicaid patients by 1.2 percentage point, which amount to around 2 percent increase compared to the sample average of 62 percentage point. The estimated effect is not sensitive to the inclusion of county and state level covariates, as the coefficients are stable across columns.

Columns 4 to 9 reports heterogeneous analysis by baseline share of Medicare patients. Column 4 to 6 indicate that nursing homes that have more share Medicare patients before the regulation are more affected by the mandatory overtime regulation. The estimated impact is around 1.4 percentage point compared to 1 percentage point in column 3. This result is consistent with findings on the policy's impact on healthcare quality in [37], where the authors found more deficiency citations among treated nursing homes with higher baseline share of Medicare patients due to the stronger reliance on contract hours following the regulation. However, considering that this subgroup exhibit no significant change in RN hours in table 4, the significant increase in Medicaid patients suggests that the impact of policy on patient composition may increase in patient uncertainty. Since Medicare patient's arrival and length of stay are much more uncertain compared to Medicaid patients who usually stay at annual basis, nursing homes with higher concentration of Medicare patient may admit more Medicaid patients as a more stable source of income.

Nursing homes with baseline Medicare patients (column 7 to 9) below third quantile increased share of Medicaid patient by around 1 percentage point on average. The event study results for both subgroups are shown in appendix figure A.2. The figure indicates no significant pre-trend in group with lower baseline share of Medicare patients that would violate identification using equation (9). Moreover, both groups experienced dynamic treatment effect that grows over years after the implementation of overtime regulation.

7 Supplemental Analysis

7.1 Total Number of Patients

One of limitation in my analysis is that I do not directly observe facilities' actual usage of contract nurses and exact number of patients admitted by their payment types. As discussed in section 4.1, I use total staff RN hours per patient day as a proxy for usage of contract hours and share of Medicaid patients among current patients as a proxy for share of Medicaid patients in newly admitted patients.

However, the validity of these two proxies relies on the assumption that the mandatory overtime regulation has no significant impact on total number of patients. Facilities could find it more cost-effective to downsize the overall operating scale and choose to serve less patients when the regulation limit their ability to use overtime hours. In this case, the results in table 5 reflects not a substitution between Medicare and Medicaid patients, but a reduced access for all types of patients. On the other hand, nursing homes could seek higher revenue by admitting more Medicaid patients without declining Medicare admissions (i.e. the total number of patients is increased), since additional Medicaid patients might just need minor amount of care from LPNs or CNAs. This means the reduction in staff RN hours per patient day could be driven by increase in denominator rather than numerator, and the increased Medicaid patient is not crowding out potential Medicare patients.

Intuitively, the number of patients is unlikely to change by the policy for two reasons. First, the occupancy rate among nursing homes is high at the baseline. Unless the baseline staff-to-patient ratio is sufficiently high from the minimum ratio that I assumed to be fixed in section 3, increasing number of patients from a high occupancy level would require more expenses on contract hours, or causing the staff-to-patient ratio to fall below the lower bound, which may incur regulation penalty or lose patients that have a strong preference for quality. Second, reducing total number of patients is not likely to be cost-effective as the property space and number of beds are fixed in the medium to long term. Facilities still need to pay the same amount of rent or mortgage regardless of number of beds and actual number of patients. One possible solution would be converting shared rooms to single rooms and serve more profitable patients (e.g. private-paying patients). However, this would result in opposite direction of change in share of Medicaid patients as reported in table 5, since Medicaid generally only reimburses for shared room.

I further confirm that the mandatory overtime regulation has no impact on total number of patients following the same method discussed in section 4.1. Figure 8 shows estimated coefficients on intersection terms in equation (12), where outcome on the left hand side is logarithm of total number of patients at facility-year level. The results indicate no significant change in number of patients before and after the policy intervention between treated and control group. The standard error of estimations increased after the regulation, which suggest potential variation in facilities' response to the regulation. Figure A.3 shows event study results by baseline share of Medicare patients. Both subgroups had no significant overall change in number of patients, but the after-treatment coefficients are some opposite directions. Facilities that are more specialized in treating Medicare patients at baseline increased number of patients immediately after the regulation, but the impact faded in the following event years and became insignificant. Since I do not observe actual patient level admissions, I am uncertain about whether this slight increase implies that the treated facilities are admitting more Medicaid patients after the policy. Table 6 reports estimation results from equation (9). Consistent with the event study results, I found no significant impact on total number of patients, but the direction of estimates is in the opposite direction between facilities with low and high baseline share of Medicare patients.

7.2 Robustness Test

In this section I test for the sensitivity of estimated increase in share of Medicaid patients regarding to the chosen maximum variance threshold parameter used in matching algorithm introduced in section 4.1. As the regulation's impact on nursing home's staffing level is well tested in [37] using facility administrative data and further confirmed in this paper using different matching method, I only test for robustness of estimation on share of Medicaid patients. To illustrate again, my matching algorithm calculate the pre-period variance of outcome distance between focal treated facility and each potential control facilities in the donor pool and select the control states that have the variance smaller than certain threshold. My main analysis used a rule of thumb value $k = 4$, which amounts to around $\frac{1}{5}$ of standard deviation of share of Medicaid patients in my unmatched whole sample. A smaller threshold thus returns better comparison group as the parallel trend assumption is more likely to hold when the outcome distance between treated unit and the control unit is smaller, while a larger threshold can return larger sample size and thus higher identification power. I therefore test for robustness using one smaller threshold and two larger threshold on whole matched sample, using full specification in equation 9.

Table 7 reports the results of this practice. Column 1 reports the similar result as in column 3 of table 5 for comparison. Column 2 reports results using smaller threshold parameter $k = 4$. The sample size decreased substantially as the number of facilities dropped by 1581. However, the average share of Medicaid patients and estimated impact from overtime regulation has no significant change. Column 3 and 4 reports result using larger threshold parameter $k = 8$ and $k = 16$ respectively. Although the sample size increased substantial from column 1 to column 4, the estimated impact and sample average of Medicaid patients share remains stable. Since k value of 16 in column 4 is around $\frac{3}{4}$ of standard deviation of Medicaid patients share in the unmatched sample (22 percentage point), I consider my estimated impact of patient composition is robust in larger samples. The event study results for samples used in column 1 to 4 are reported in figure A.4. Similar to figure 7, the figures indicate no significant trends between treated and control group before the mandatory overtime regulation, and increasing dynamic treatment effect since event year 0.

8 Conclusions

This paper investigates the relationship between nursing home's nursing staff level and patient composition. I leveraged on an exogenous shock to nursing home's ability to usage overtime hours caused by state level regulations prohibiting mandatory overtime for nurses. My identification strategy applies a matching algorithm at facility level based on pre-periods outcome trend to select qualified control units for each treated facility and runs a difference-in-difference model to estimate the regulation's average impact on nursing home's total RN hours per patient day and share of Medicaid patients. I found prohibiting mandatory overtime reduces total RN hours per patient day by 2.7 percent on average. My estimate is of same direction, but smaller magnitude compared to past literature. I found the reduction in formal staff RN level leads to slightly increase in share of Medicaid patients by around 1 percentage point. I highlight the substantial variation in nursing home's patient composition and the corresponding difference in other characteristics. Heterogeneity analysis implies that nursing homes with top quantile baseline share of Medicare patients have no significant change in total staff RN hours but larger increase in share of Medicaid patients (around 1.4 percent) compared to the overall sample.

The estimated impact on both RN hours and Medicaid patients share is lower among nursing homes that were treating disproportionally more Medicare patients before the policy implementation.

Overall, the empirical results are consistent with my hypothesis on relationship between nursing home's staff level and patient composition driven by variation in labor intensity and arrival rate across patient types. As nursing homes face higher cost on more flexible labor inputs (i.e. by substituting overtime hours with contract hours), the share of Medicare patients becomes lower due to increase in marginal cost of admitting patients that are more likely to trigger overtime or contract hours. My findings indicate restricting nursing home's ability to use overtime hours can be an effective method that both improves Medicaid patient's access to long-term care and avoid the negative consequence from fatigue of nursing staff. More generally, policy makers on labor regulation and health care access should account for the heterogeneous usage of labor inputs across differential types of served populations in settings similar to the settings in this paper.

My analysis is limited and leaves room for future works in several ways. First, this paper does not include a welfare analysis due to data limitation. In particular, I do not observe nursing home's actual usage of scheduled hours due to data limitation. If nursing homes in treated states reduced overtime hours and compensate it with both using more contract nurses and hiring more formal RN staff (although the total staff hours decreases), it would be welfare improving as higher RN staff level is associated with better healthcare quality. I also do not have access to admission level data that contains individual patient characteristics to determine whether the overtime regulation compromises access to long-term care for Medicare patients that can benefit the most from high quality long-term care. If Medicare patients that requires more intensive nursing care during recovery period encounter more difficulty in being admitted to preferrable facility, the policy could have negative overall welfare impact due to potential resulting increase in rehospitalization or mortality. Second, this paper focus on nursing homes that existed from 2000 to 2013 and thus only investigates the overtime regulation's impact on nursing home's patient composition at intensive margin instead of extensive margin. Since the regulation raises overall labor cost, nursing homes may exist local market hiring additional RN staff is difficult or the expected revenue from Medicaid patients is too low. Future works should examine the regulation's impact on hazard of nursing home closures in treated states, and identify the areas that have more loss of facilities. If areas with higher share of Medicaid-eligible populations tend to experience more facility closures, it would suggest the policy may exacerbate the overall access inequality issue.

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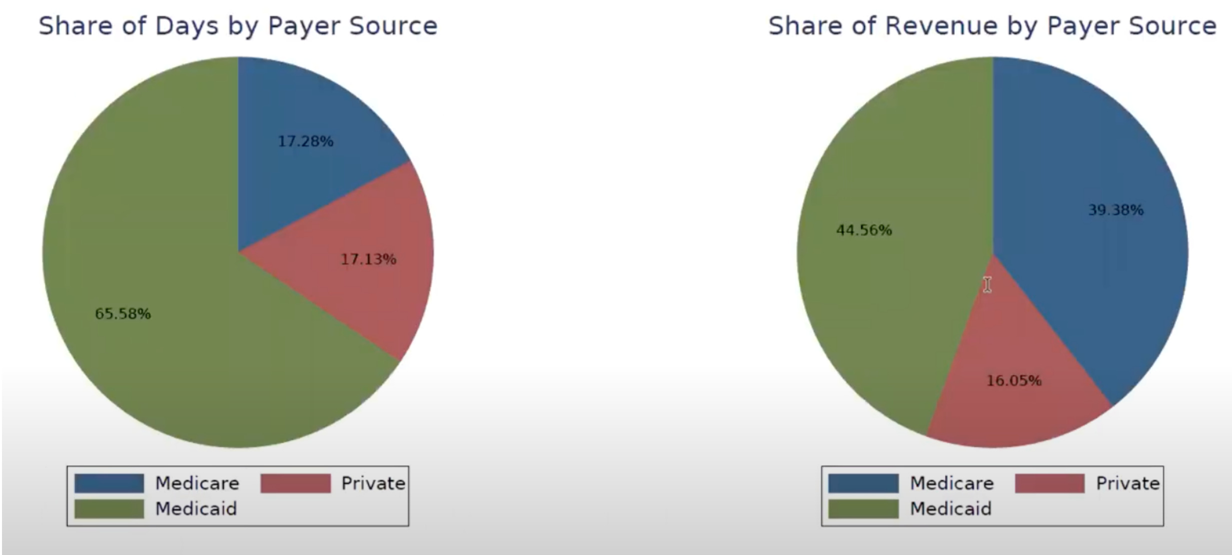
Figures and Tables

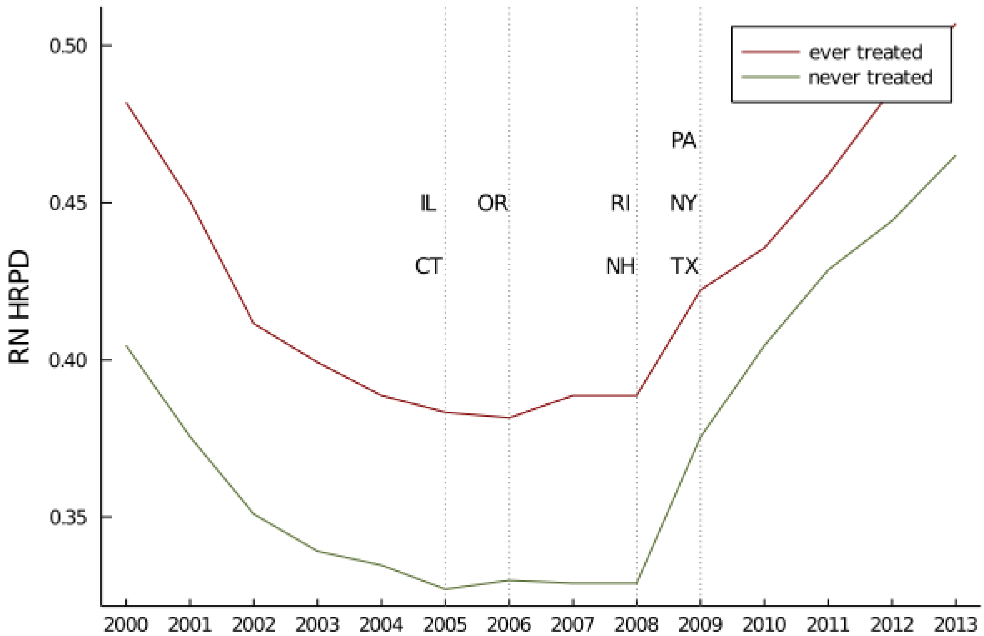
Figure 1: Composition of Nursing home's patient payment sources and revenue sources



Source: [25]

Figure 2: Outcome trends across calendar year

(a) RN hours per patient day



(b) Share of Medicaid patients

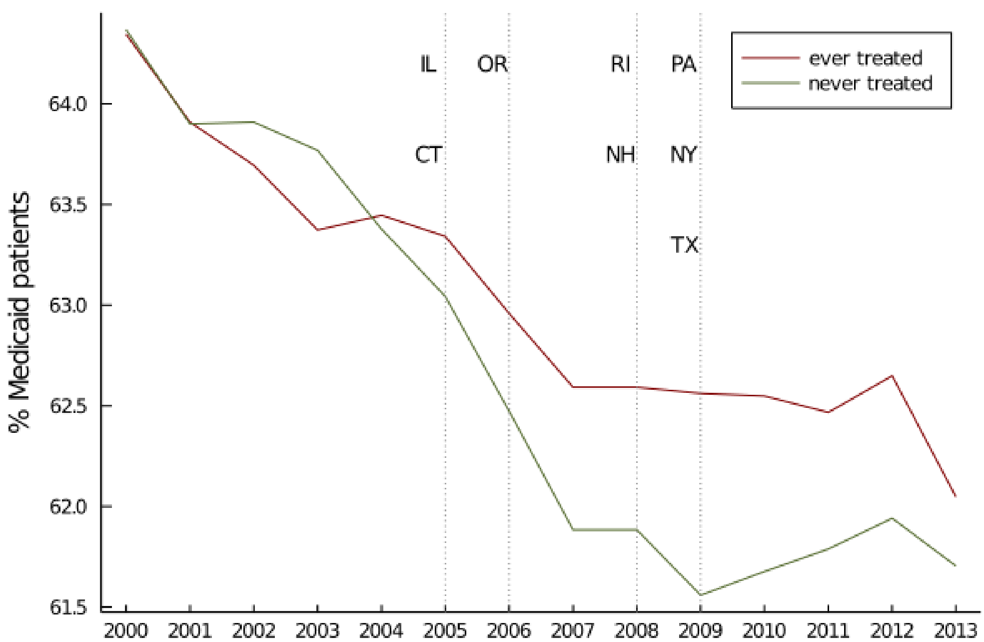


Figure 3: Number of patients across calendar years

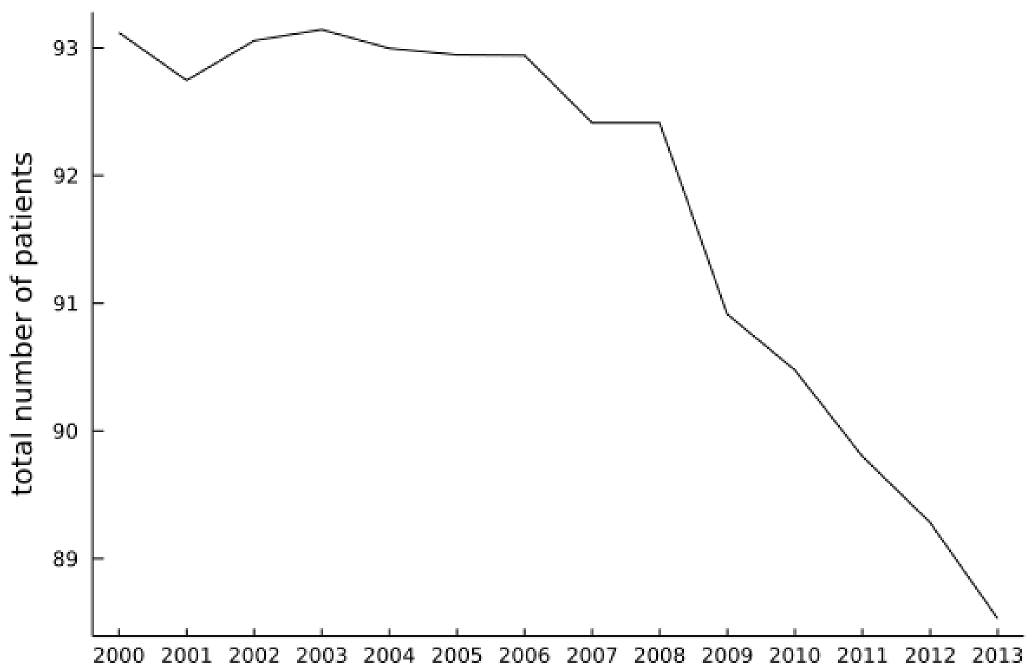


Figure 4: Nursing Home's share of Medicare patients in 2004

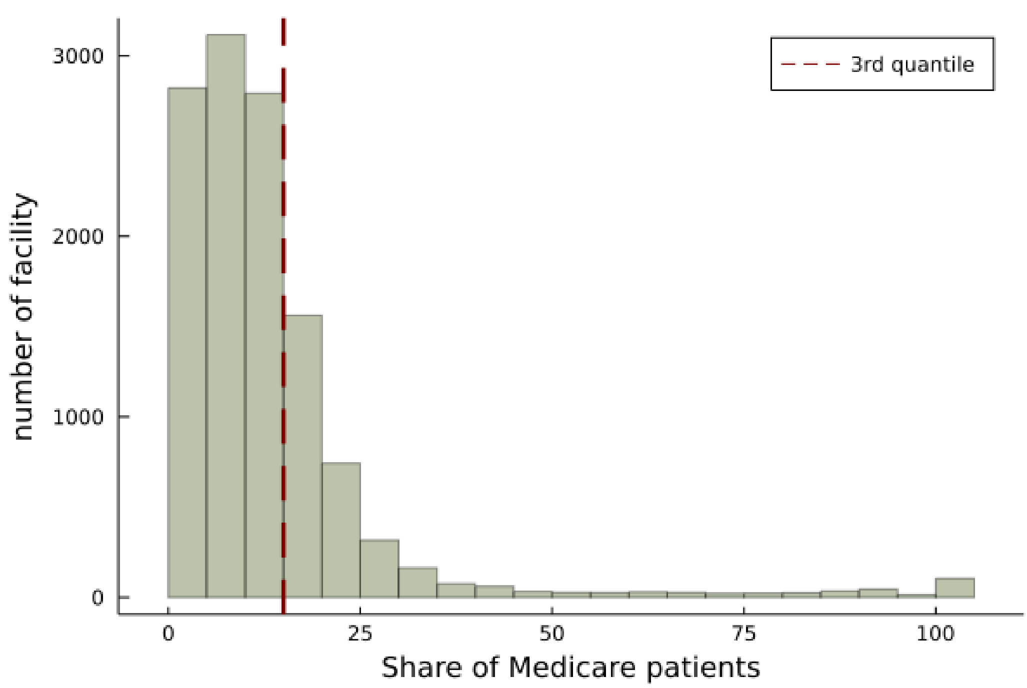
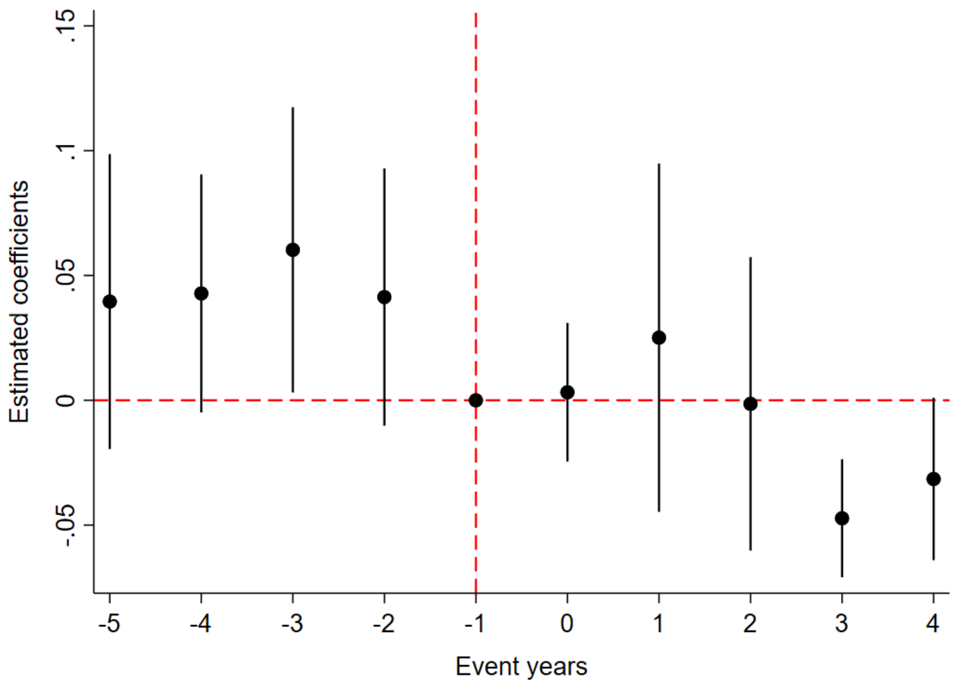


Figure 5: Event study on treated facilities in unmatched sample

(a) RN hours per patient day



(b) Share of Medicaid patients

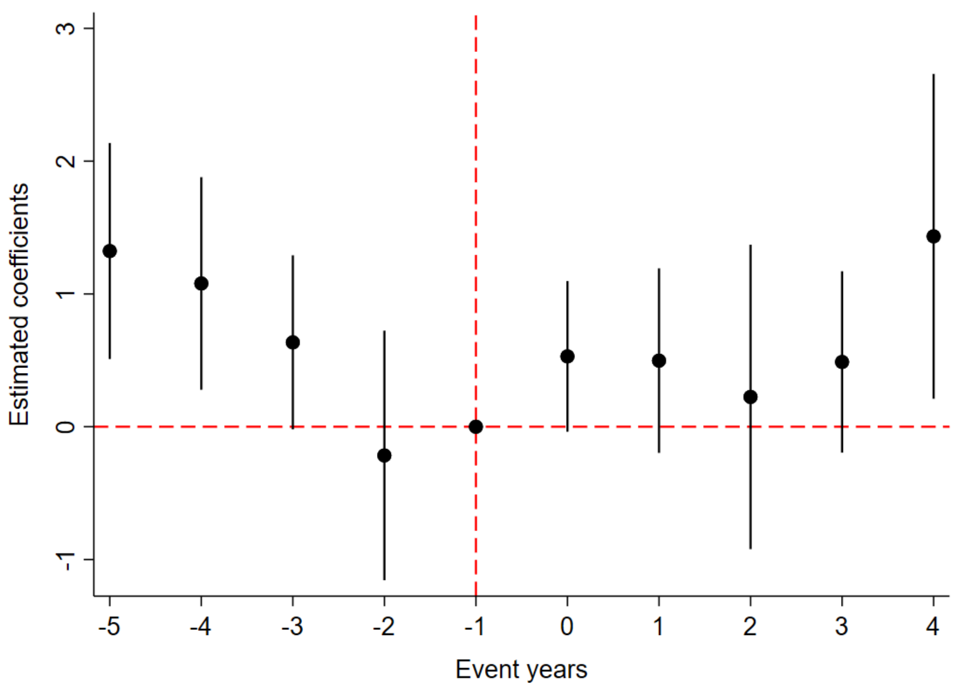
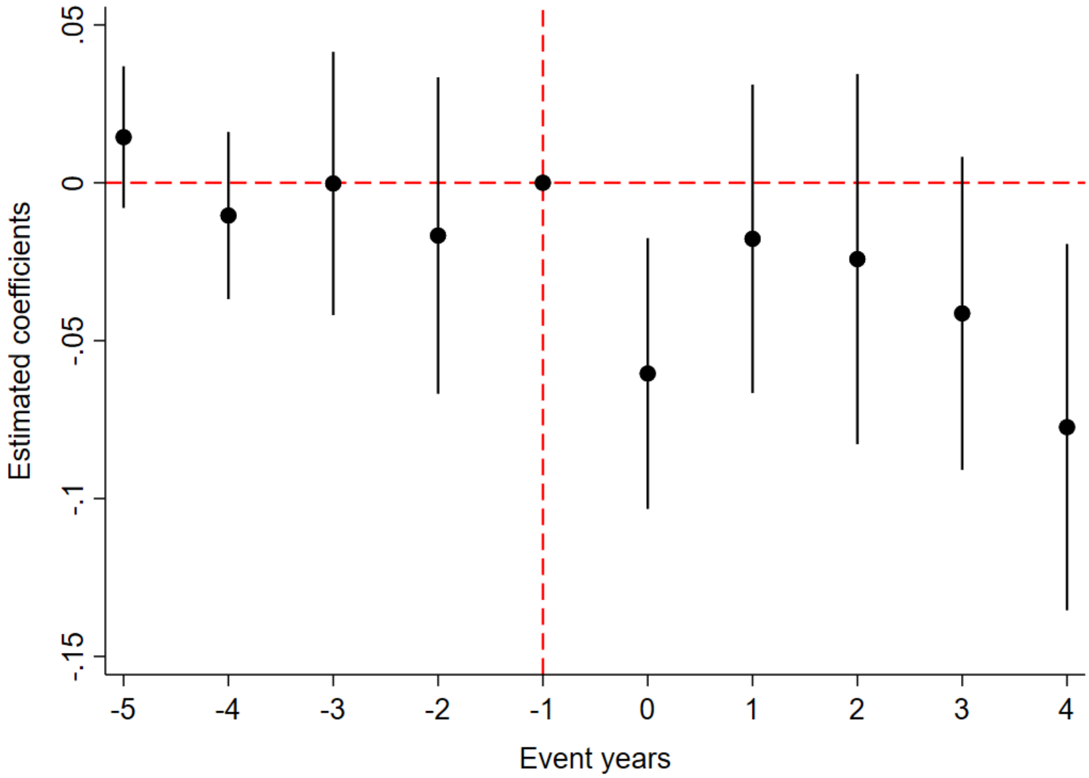
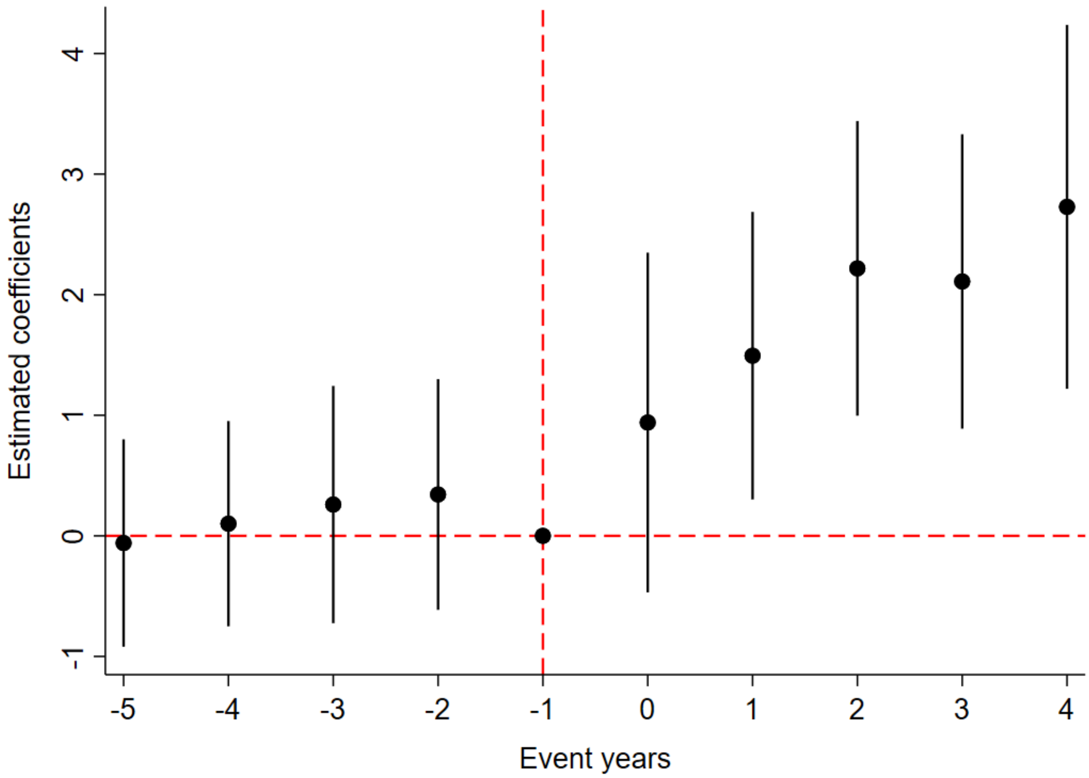


Figure 6: Total formal staff RN hours per patient day



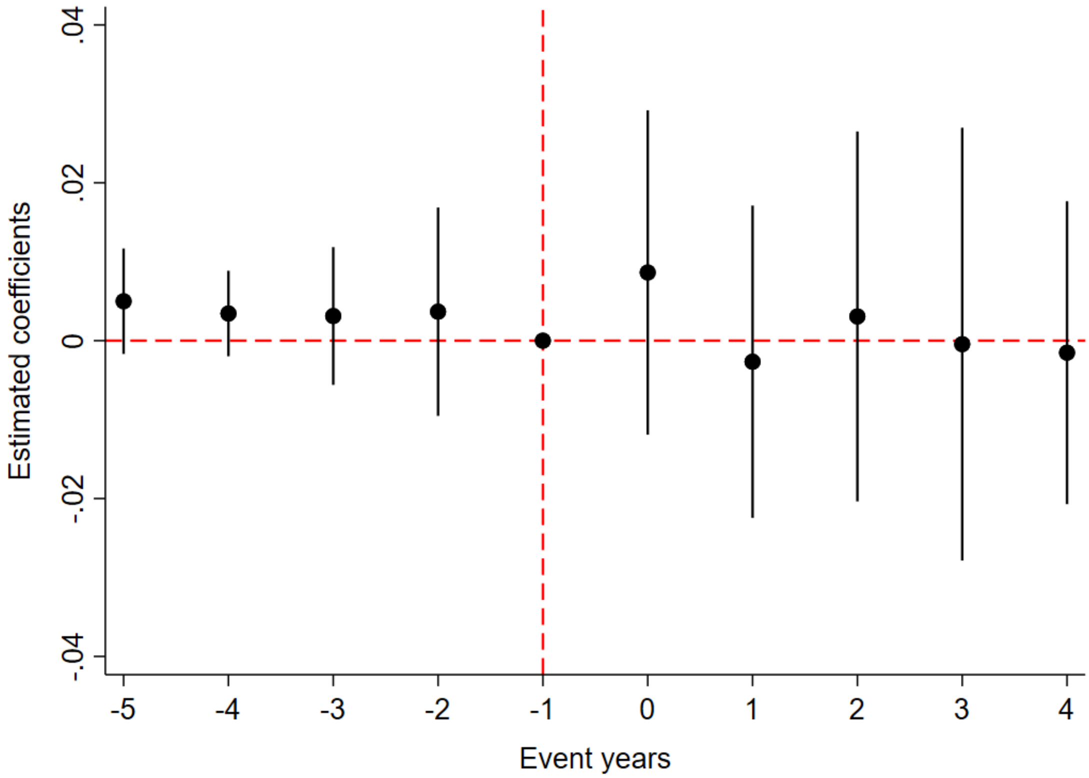
Note: Controlled county characteristics include: population, share of senior population, share of black population, income per capita, rural status, number of hospital beds in the county for every 1000 persons age 65 or older, number of home health agencies in the county for every 1000 persons age 65 or older, Medicare managed care organization penetration rate. State level policy controls include Medicaid bed hold and Medicaid case mix. To keep balanced panel, sample restricted to observations with event years -5 to 4; standard errors clustered at county level.

Figure 7: Share of Medicaid patients



Note: Controlled county characteristics include: population, share of senior population, share of black population, income per capita, rural status, number of hospital beds in the county for every 1000 persons age 65 or older, number of home health agencies in the county for every 1000 persons age 65 or older, Medicare managed care organization penetration rate. State level policy controls include Medicaid bed hold and Medicaid case mix. To keep balanced panel, sample restricted to observations with event years -5 to 4; standard errors clustered at county level.

Figure 8: Total number of patients



Note: Controlled county characteristics include: population, share of senior population, share of black population, income per capita, rural status, number of hospital beds in the county for every 1000 persons age 65 or older, number of home health agencies in the county for every 1000 persons age 65 or older, Medicare managed care organization penetration rate. State level policy controls include Medicaid bed hold and Medicaid case mix. To keep balanced panel, sample restricted to observations with event years -5 to 4; standard errors clustered at county level.

Table 1: Policy timing and provisions by states

State	Year of implementation	Shfit length cap and Respite requirements
California	2001	12 hours in any 24 hours period
Maine	2001	10 consecutive resting hours after working any overtime shift
Minnesota	2002	12 hours in any 24 hours period
Washington	2002	Extension beyond predetermined scheduled hours is prohibited unless under emergency or scenarios where critical skill needed
Maryland	2002	Extension beyond predetermined scheduled hours is prohibited unless under emergency or scenarios where critical skill needed
New Jersey	2003	Hours per week cannot exeed 40
West Virginia	2004	16 hours in any 24 hours period; 8-hour requested rest after any 12 hours shift
Connecticut	2005	Overtime hours beyond predetermined scheduled hours is prohibited unless under emergency or scenarios where critical skill needed
Illinois	2005	Overtime hours capped at 4 hours even under emergency; 8-hour requested rest after any 12 hours shift
Oregon	2006	12 consecutive hours; hours per week cannot exceed 48; shift extension capped at 4 hours even under emergency
Rhode Island	2008	12 consecutive hours
New Hampshire	2008	12 consecutive hours
Texas	2009	Extension beyond predetermined scheduled hours is prohibited unless under emergency or scenarios where critical skill needed
Pennsylvania	2009	Extension beyond predetermined scheduled hours is prohibited unless under emergency or scenarios where critical skill needed
New York	2009	Extension beyond predetermined scheduled hours is prohibited unless under emergency or scenarios where critical skill needed
Alaska	2010	14 consecutive hours
Massachusetts	2012	12 consecutive hours in any 24 hours period

Table 2: Descriptive statistics across samples

	whole sample		matched sample			
			RN HRPD (k=0.005)		% Medicaid patients (k=8)	
	ever treated	never treated	ever treated	never treated	ever treated	never treated
Facility						
# facility	3641	8461	3317	8104	2824	7716
RN hours per patient day	0.43	0.38	0.34	0.32	0.45	0.38
	(0.64)	(0.56)	(0.33)	(0.32)	(0.68)	(0.57)
# patients	104.59	85.93	109.22	88.09	108.40	86.93
	(65.38)	(44.33)	(65.26)	(43.75)	(66.89)	(44.63)
% Medicaid patients	62.95	62.49	65.64	64.29	62.38	62.86
	(22.86)	(20.82)	(19.50)	(18.77)	(23.72)	(20.97)
# beds	123.99	101.89	129.05	103.98	127.72	102.43
	(69.83)	(49.86)	(69.25)	(49.06)	(71.50)	(49.91)
for profit	0.69	0.69	0.70	0.70	0.67	0.68
	(0.46)	(0.46)	(0.46)	(0.46)	(0.47)	(0.46)
County						
log(population)	12.40	11.56	12.40	11.52	12.50	11.53
	(1.72)	(1.62)	(1.72)	(1.62)	(1.69)	(1.61)
% aged over 60	18.85	19.57	18.51	19.28	18.50	19.27
	(4.10)	(4.76)	(4.03)	(4.72)	(3.91)	(4.73)
% black population	10.48	12.52	10.64	12.39	10.68	12.38
	(9.85)	(14.69)	(9.98)	(14.70)	(10.06)	(14.71)
income per capita	36,780.57	33,102.96	35,637.62	32,063.01	36,361.68	32,160.05
	(11,934.57)	(8,421.23)	(11,511.79)	(8,256.54)	(11,944.98)	(8,331.68)
# beds per 1000 population	26.35	27.60	25.95	27.67	25.95	27.60
	(17.50)	(24.14)	(16.62)	(24.47)	(16.18)	(24.40)
# home care per 1000	0.29	0.27	0.28	0.27	0.27	0.27
	(0.33)	(0.28)	(0.30)	(0.28)	(0.29)	(0.28)
% managed care beneficiaries	17.62	13.38	16.28	11.65	16.42	11.68
	(15.11)	(12.55)	(14.92)	(12.24)	(14.97)	(12.24)
State						
CaseMix	0.88	0.65	0.87	0.64	0.86	0.65
	(0.33)	(0.48)	(0.34)	(0.48)	(0.35)	(0.48)
BedHold	0.62	0.87	0.60	0.88	0.65	0.87
	(0.49)	(0.33)	(0.49)	(0.33)	(0.48)	(0.33)
Observations	61,297	143,602	44,659	112,599	39,461	107,861

Table 3: Descriptive statistics by 3rd quantile share of Medicare patients in 2004

	(1) above q3	(2) below q3	(3) difference
Facility			
# Facility	2997	9077	
RN hours per patient day	0.55	0.28	0.27***
	(0.93)	(0.27)	(0.00)
# patients	90.81	93.67	-2.86**
	(49.35)	(54.02)	(0.01)
% Medicaid patients	47.83	68.54	-20.71***
	(23.97)	(17.80)	(0.00)
# beds	104.13	109.78	-5.64***
	(53.09)	(59.27)	(0.00)
for profit	0.74	0.65	0.09***
	(0.44)	(0.48)	(0.00)
hospital based	0.11	0.05	0.06***
	(0.31)	(0.21)	(0.00)
County			
Population	563,944	427,157	136,787***
	(916,825)	(830,478)	(0.00)
% population aged over 60	18.30	18.73	-0.43***
	(4.85)	(4.33)	(0.00)
% black population	12.28	11.51	0.77***
	(12.07)	(13.83)	(0.01)
annual income per capita	32,772.62	30,786.90	1,985.71***
	(8,179.15)	(7,729.48)	(0.00)
# beds per 1000 population	27.52	27.66	-0.14
	(20.24)	(23.81)	(0.78)
# home care facility per 1000	0.24	0.27	-0.03***
	(0.20)	(0.27)	(0.00)
% managed care beneficiaries	8.60	8.52	0.08
	(11.00)	(11.76)	(0.73)
State			
CaseMix	0.69	0.76	-0.08***
	(0.46)	(0.43)	(0.00)
Bedhold	0.69	0.72	-0.04***
	(0.46)	(0.45)	(0.00)
Observations	2,997	9,077	12,074

Table 4: Formal RN staff level

Dependent var: log(RN hours per patient day)

	whole matched sample			Baseline %Medicare above q3			Baseline %Medicare below q3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
regulation	-0.028*	-0.026*	-0.027*	0.005	0.006	0.005	-0.047***	-0.045***	-0.046***
	(0.014)	(0.014)	(0.014)	(0.018)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
sample mean	0.327	0.327	0.327	0.352	0.352	0.352	0.304	0.304	0.304
N	110196	110196	110196	42922	42922	42922	89260	89260	89260
R^2	0.695	0.695	0.695	0.690	0.690	0.690	0.686	0.687	0.687
facility FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
county controls		Y	Y		Y	Y		Y	Y
state controls			Y			Y			Y

Note: Controlled county characteristics include: population, share of senior population, share of black population, income per capita, rural status, number of hospital beds in the county for every 1000 persons age 65 or older, number of home health agencies in the county for every 1000 persons age 65 or older, Medicare managed care organization penetration rate. State level policy controls include Medicaid bed hold and Medicaid case mix. Sample mean reports the outcome of interest in the whole analysis sample, without logarithm.

Standard errors in parentheses, clustered at state level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Share of Medicaid Patients

Dependent var: share of Medicaid residents

	Whole matched sample			% Medicare above q3			% Medicare below q3		
	1	2	3	(4)	(5)	(6)	(7)	(8)	(9)
regulation	1.205**	1.092**	1.004**	1.602**	1.488**	1.351**	1.239**	1.114**	1.019*
	(0.499)	(0.445)	(0.462)	(0.700)	(0.589)	(0.589)	(0.520)	(0.501)	(0.526)
sample mean	62.732	62.732	62.732	54.330	54.330	54.330	66.857	66.857	66.857
N	104728	104728	104728	38214	38214	38214	81358	81358	81358
R^2	0.876	0.876	0.876	0.909	0.909	0.909	0.827	0.827	0.827
facility FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
county controls		Y	Y		Y	Y		Y	Y
state controls			Y			Y			Y

Note: Controlled county characteristics include: population, share of senior population, share of black population, income per capita, rural status, number of hospital beds in the county for every 1000 persons age 65 or older, number of home health agencies in the county for every 1000 persons age 65 or older, Medicare managed care organization penetration rate. State level policy controls include Medicaid bed hold and Medicaid case mix. Sample mean reports the outcome of interest in the whole analysis sample, without logarithm.

Standard errors in parentheses, clustered at state level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Total number of patients

Dependent var: log(number of patients)

	whole matched sample			Baseline %Medicare above q3			Baseline %Medicare below q3		
	1	2	3	4	5	6	7	8	9
regulation	-0.005	-0.005	-0.007	0.011	0.011	0.012	-0.011	-0.010	-0.013
	(0.008)	(0.008)	(0.008)	(0.018)	(0.019)	(0.019)	(0.010)	(0.010)	(0.011)
sample mean	88	88	88	87	87	87	88	88	88
N	106534	106534	106534	40431	40431	40431	84097	84097	84097
R^2	0.931	0.931	0.931	0.926	0.927	0.927	0.936	0.936	0.936
facility FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
county controls		Y	Y		Y	Y		Y	Y
state controls			Y			Y			Y

Note: Controlled county characteristics include: population, share of senior population, share of black population, income per capita, rural status, number of hospital beds in the county for every 1000 persons age 65 or older, number of home health agencies in the county for every 1000 persons age 65 or older, Medicare managed care organization penetration rate. State level policy controls include Medicaid bed hold and Medicaid case mix. Sample mean reports the outcome of interest in the whole analysis sample, without logarithm.

Standard errors in parentheses, clustered at state level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Robustness of Matching parameters

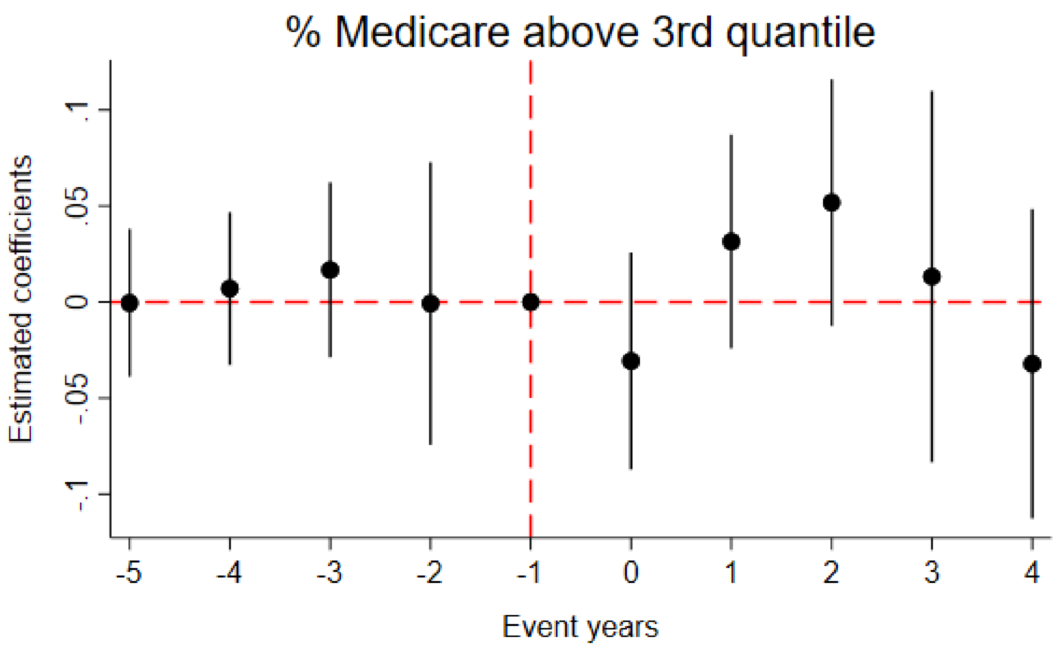
Dependent var: share of Medicaid patients	k = 8	k = 4	k = 16	k = 20
	(1)	(2)	(3)	(4)
regulation	1.004**	1.058**	0.912*	0.890*
	(0.462)	(0.424)	(0.463)	(0.467)
Sample mean	62.732	62.647	62.861	62.794
# facilities	10540	8959	11226	11395
N	104728	89013	111572	113259
R^2	0.876	0.905	0.867	0.856
facility FE	Y	Y	Y	Y
year FE	Y	Y	Y	Y
county controls	Y	Y	Y	Y
state controls	Y	Y	Y	Y

Note: Controlled county characteristics include: population, share of senior population, share of black population, income per capita, rural status, number of hospital beds in the county for every 1000 persons age 65 or older, number of home health agencies in the county for every 1000 persons age 65 or older, Medicare managed care organization penetration rate. State level policy controls include Medicaid bed hold and Medicaid case mix. Sample mean reports the outcome of interest in the whole analysis sample, without logarithm.

Standard errors in parentheses, clustered at state level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendices

Figure A.1: RN HRPD by baseline share of Medicare patients



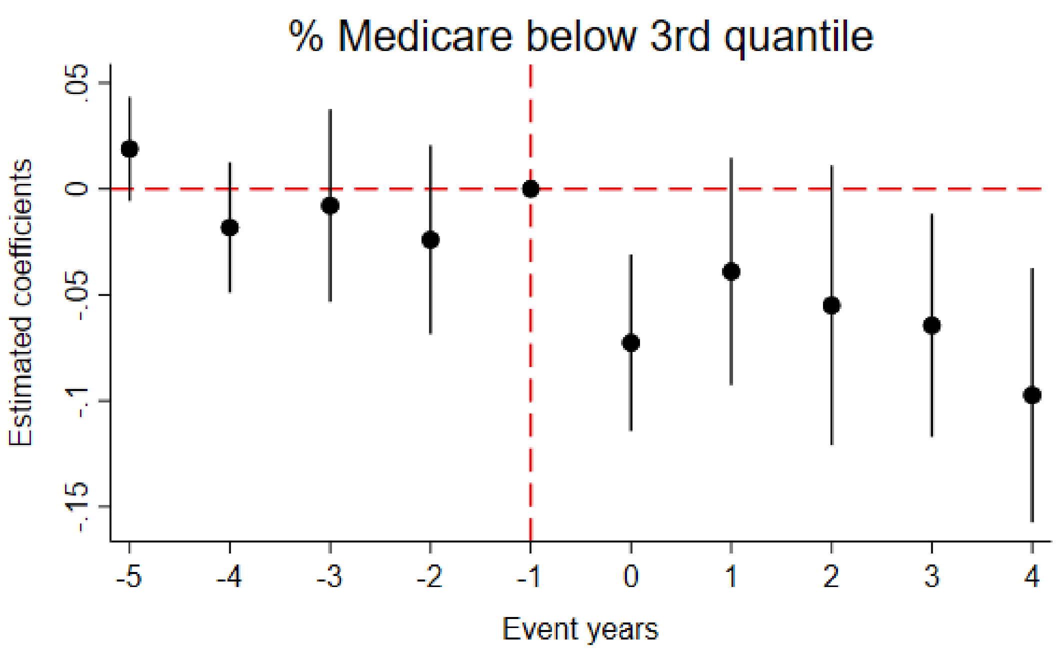


Figure A.2: Share of Medicaid patients by baseline share of Medicare patients

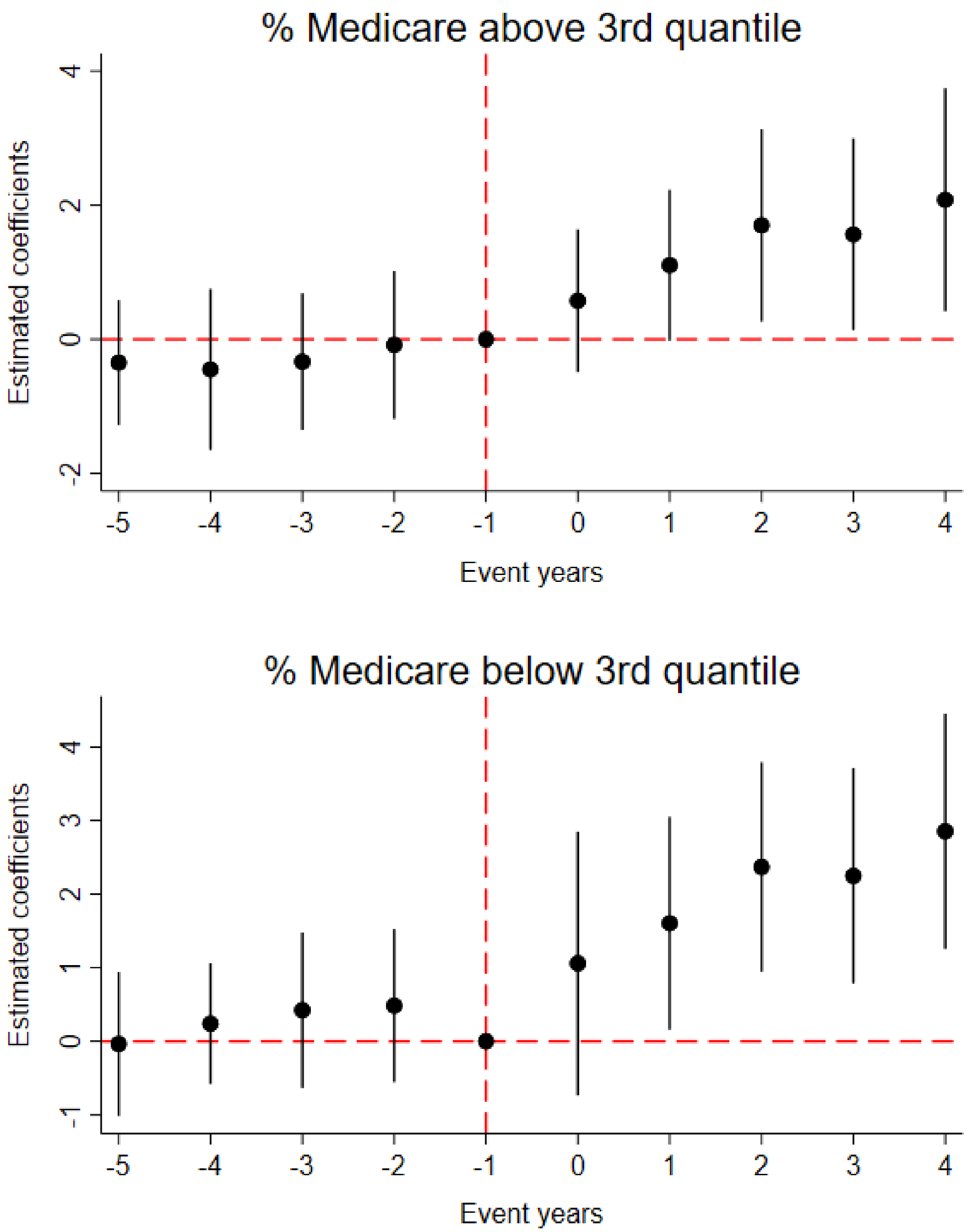


Figure A.3: Total number of patients by baseline share of Medicare patients

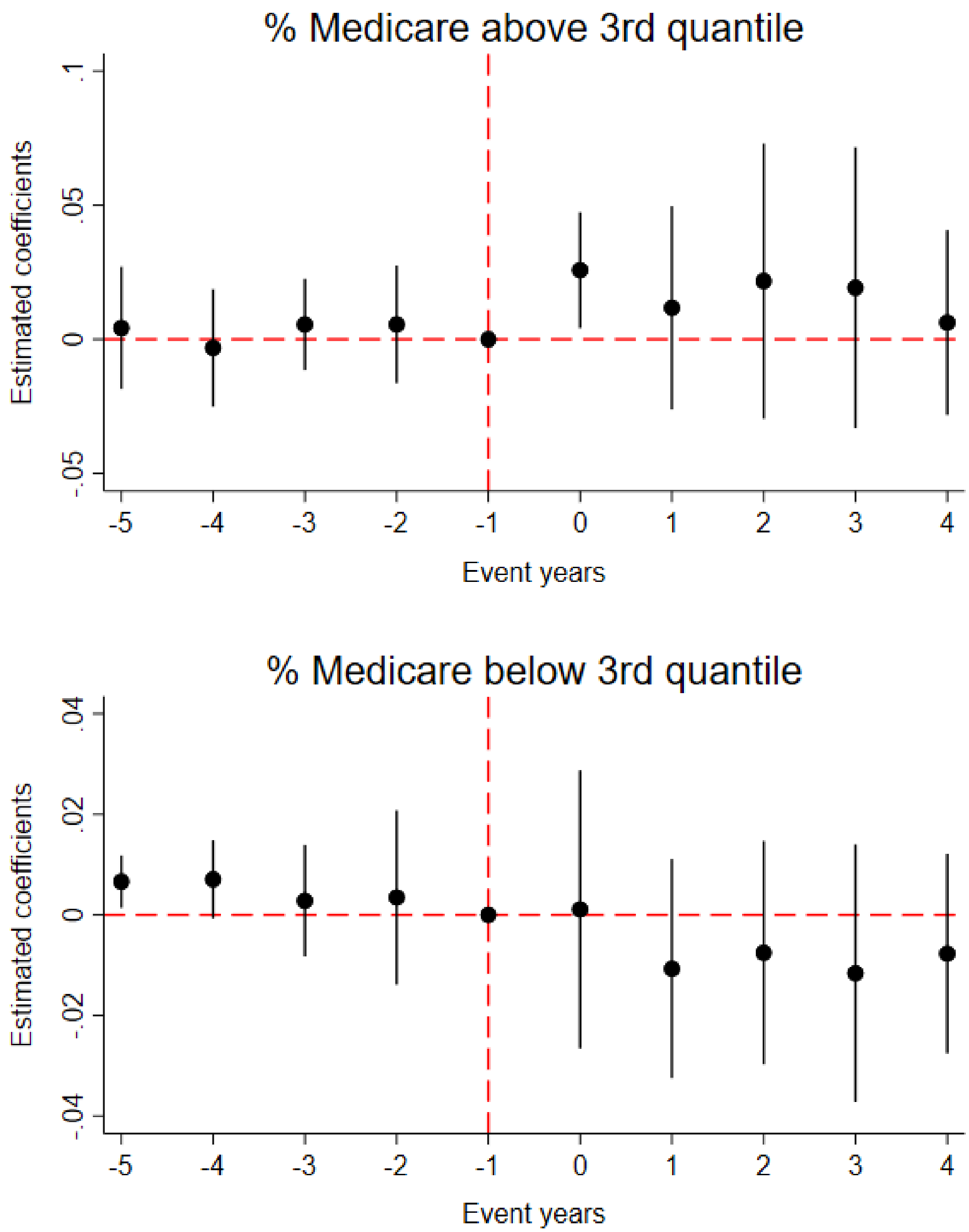
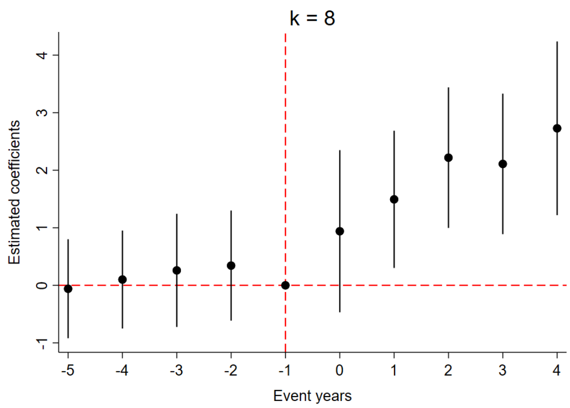
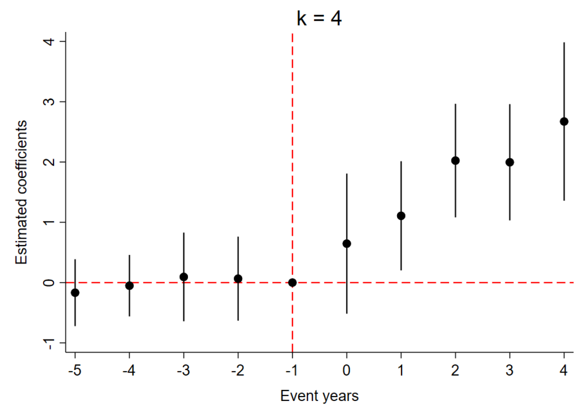


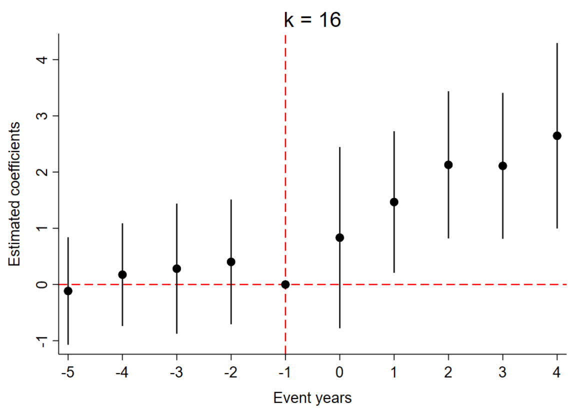
Figure A.4: Estimates on share of Medicaid patients by matching threshold parameter



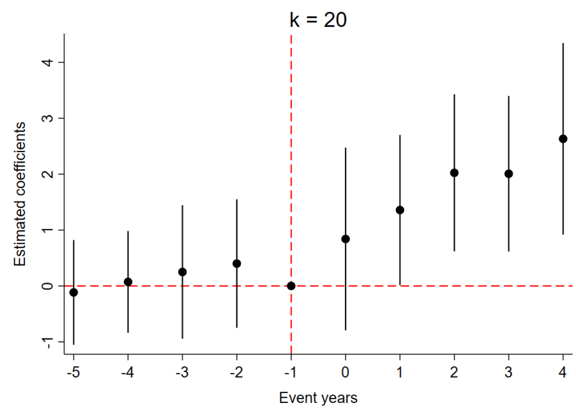
(a) Network 1



(b) Network 2



(c) Network 3



(d) Network 4