Minimum Wages and Employment Composition*

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Abstract

This paper examines how minimum wages change the allocation of hours across workers and the nature of low-wage work. We leverage information on more than 700 million daily worker shifts covering the entire US nursing home industry over the 2016-2019 period matched to more than 300 state, county, and city minimum wage changes. Higher minimum wages shift the allocation of hours at the firm level towards workers with high levels of firm-specific experience. The shift in the allocation of hours is due to greater retention amongst the most experienced workers and increased hours worked by individual workers. These hours responses undo about 40 percent of the estimated relative earnings gains between workers in the first and third terciles of experience. Therefore, while higher wages increase the experience-adjusted amount of services provided, which may improve the consumer experience, they also attenuate relative earnings gains for new workers.

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1 Introduction

Minimum wages mechanically weakly increase workers' hourly pay, but the overall effect on earnings is ambiguous as any reductions in employment, hours worked, or non-wage compensation offset the hourly wage gains. The net effect of employment and wages may vary by workers' occupation or experience, or differ across the pre-reform income distribution. Although much work has examined the aggregate responsiveness of low-wage employment to minimum wages increases, there is less known about how minimum wages affect which workers firms employ, how employers allocate hours across those workers, and how minimum wages change the nature of work.

Distributional considerations are of first-order importance in drawing conclusions about the effects of higher minimum wages and the overall effect on the labor market from a social welfare standpoint, as well as informing our understanding of how government interventions shape the nature of work, for at least two reasons.

First, minimum wages increase hourly pay for the lowest-paid employees – new hires and those in low-wage occupations – and reduce the relative cost of high-wage and experienced employees. Accordingly, employers may allocate hours to their more experienced or skilled workers and away from recent hires, contract workers, part-time workers, and poorly performing employees. Such changes in the labor mix could increase overall income inequality and diminish any earnings gains from higher hourly wages.

Second, higher minimum wages can also change the nature of low-wage work on several dimensions. For example, a higher minimum wage could incentivize employers to better retain their most preferred employees (defined by experience, skill, or occupation) or to fire less-preferred employees. Such practices would improve average match quality and could improve overall performance. Firms could also adjust their recruiting practices, reduce the intensity with which they hire low-wage employees or change the types of workers they hire. They might also change scheduling practices, their reliance on part-time or full-time staff, or the use of overtime hours.

Despite these myriad possible responses, the existing work on distributional effects of minimum wage increases is relatively small in comparison to evidence on aggregate effects, and how higher wages change the nature of low-wage jobs is even more nascent. This paper broadens our understanding of how higher minimum wages change the low-wage workplace in terms of the composition of employment and the nature of work. We examine these questions in the context of the nursing home sector, a labor-intensive, low-wage industry, and leverage daily employee-level data for the entire industry. The granularity of these data, covering more than 15,000 facilities and 700 million worker shifts, provide nuanced insights into how minimum wages affect low-wage employment.

Our findings are threefold. First, we find no disemployment effect among nursing home workers; rather, higher minimum wages increase the number of certified nursing assistants (CNAs) and the hours worked by these employees. The patterns we observe are consistent with higher minimum wages enabling firms to retain more low-wage workers and shift their workforce away from contract employees to in-house hires. We also find modest effects of a compositional shift towards credentialed nurses (LPNs), reflecting the lower relative costs of employing these workers.

Second, the hours allocation of CNAs within a firm shifts away from new hires towards workers who have high levels of firm-specific experience before the higher wage becomes effective. This change in the overall allocation of hours is a combination of the number of workers and the hours each worker works. Higher minimum wages increase retention among tenured workers, and the workers who are retained tend to work more hours after the minimum wage increases than they worked before the wage increase.

Third, we provide some of the first empirical evidence showing how minimum wages affect the nature of low-wage work. We find that these changes vary across the experience distribution: relatively inexperienced workers are more likely to work part-time roles, whereas workers that have been with the firm the longest transition to full-time work. Whereas average hours increase among all workers who were employed before the higher wage became effective, the hours and overtime gains are largest for the most experienced workers. Therefore, although minimum wages compress wage inequality at the lower tail of the income distribution, increased gaps in weekly hours between relatively less-experienced and experienced workers offset approximately 40 percent of the mechanical decrease in earnings inequality.

We use our estimates to simulate how a \$1 a year increase in the minimum wage would affect the long-run equilibrium employment composition. These simulations show a pronounced long-run effect of a \$1 minimum wage increase, with the percentage of hours of patient care received from workers with greater than 2,000 hours of firm-specific experience (approximately equivalent to one year of full-time employment) increasing by 8 percentage points (approximately 15 percent). This exercise illustrates that minimum wages can be an effective tool to reduce nursing staff turnover and increase tenure in the long-run.

This paper makes several contributions to the existing literature. First, a large body of work examines how higher minimum wages affect employment levels and the number of hours worked. We contribute to this literature by examining how the minimum wage affects employment in a low-wage industry that has received relatively little attention to date. In addition, by drawing on variation in more than 300 reforms over a three-year period, we overcome many concerns about external validity present in analyses of a single, local reform. Finally, our measure of hours worked is reported with high accuracy from data subject to audit; accordingly, attenuation bias is less of a concern in our setting than in studies relying on self-reported hours worked from household surveys. That we find higher minimum wages increases low-wage employment, measured by number of workers and hours worked is consistent with minimal aggregate disemployment effects documented in the previous literature (summarized by Schmitt (2013), Belman and Wolfson (2014), and Dube (2019a)).

Second, our finding that higher minimum wages reduce worker flows contributes to a growing literature examining the effect of minimum wages on worker flows and labor market churn. Consistent with previous work, we find that higher minimum wages lower the separatopms rate (Portugal and Cardoso, 2006; Gittings and Schmutte, 2016; Dube et al., 2016; Jardim et al., 2020). Building on this work, we provide some of the first evidence on which workers are retained and the dynamics of worker flows. We find that the reductions in separations are increasing in firm-specific experience: a 10 percent increase in the minimum wage reduces turnover among the most experienced workers by about 20 percent for the representative firm. Greater retention, particularly in the healthcare sector, has the potential to benefit not only firms, but the consumers they serve. Existing work finds that higher turnover is correlated with lower nursing home quality (Gandhi et al., 2021) and increasing retention improves patient outcomes in both hospital (Bartel et al., 2014) and nursing home (Antwi and Bowblis, 2018) settings. Therefore, our findings provide a mechanism for how higher wages can improve service quality in nursing homes (Ruffini, 2020).

Third, previous work finds that higher minimum wages reduce lower-tail inequality and poverty in the cross-section (Autor et al., 2016; DiNardo et al., 1996; Lee, 1999; Lemieux, 2008; Dube, 2019b). However, among low-wage workers, the patterns are more nuanced. We build upon the literature examining the distributional effects of minimum wages by examining how these changes affect the allocation of hours across workers with varying degrees of firm-specific experience. In doing so, this work is closely related to studies examining the distributional effects of a single minimum wage change (Jardim et al., 2020; Giuliano, 2013) or several local changes (Gopalan et al., 2021), as well as studies examining earnings growth of low-wage workers over longer periods (Clemens and Wither, 2019; Rinz and Voorheis, 2018). Our results show that higher minimum wages prompt firms to alter the allocation of hours towards workers with high levels of firm-specific experience, consistent with studies examining the effects of recent case-study changes (Jardim et al., 2020; Gopalan et al., 2021). We extend the existing literature by examining the dynamics of these changes up to nine months after a minimum wage reform and document that hours reallocation towards more experienced workers grows throughout this time period. In addition, we provide some of the first evidence on scheduling practices that drive this reallocation, and find that greater hours worked by tenured workers is a combination of increases in both overtime and regular hours. In addition, week-to-week scheduling patterns for these workers become less volatile.

The rest of this paper proceeds as follows. Section 2 outlines a conceptual framework explaining how employers may respond to higher labor costs. Section 3 overviews the data and empirical framework. Section 4 presents results and Section 5 concludes.

2 Conceptual framework

We focus our analysis and discussion on markets with substantial competition in the labor market for nursing home staff, as employers that are the only firm in their labor markets may face different incentives.[1]

We consider a simple framework where firms use numerous types of labor, defined by skill and experience. Minimum wages change the relative costs of different labor types by increasing relative costs of newly-hired workers and those in low-wage occupations. Accordingly, firms are expected to substitute away from

[1] We define "low concentration" as a labor market having a Herfindahl Index below 0.2. See the Technical Appendix A.1 for details on how this measure is created.

minimum wage labor to factors that are substitutes in production for these workers, including workers in higher-paid occupations or those with long tenures in the same occupation who are likely to receive an experience premium.

In our setting, nursing homes are labor-intensive industries with little scope for labor-capital substitution in the short-term. Higher minimum wages in this sector are expected to shift employment and the allocation of hours away from new hires and towards incumbent workers, and away from CNAs towards vocational nurses. We do not, however, expect substantial shifts towards workers with job tasks substantially different from CNAs– namely registered nurses.

There are two primary ways in which employers may shift their allocation workers – and accordingly, their labor costs – in response to a binding minimum wage. These responses can be conceptualized as an extensive margin, or "retention" response, and an intensive margin, or "individual worker" response.

Retention effect First, higher minimum wages could affect worker flows, and therefore retention. Increases in the relative cost of new hires and reduced asset value of vacancies incentivize firms to rely more heavily on more-experienced workers (Brochu and Green, 2013). Overall, in models with on-the-job search, compression in the lower tail of the earnings distribution from higher minimum wages reduces the arrival rate of higher-paying jobs (Dube et al., 2016). By a symmetric argument, if the separation rate of firm i falls, the hiring rate of peer firm j is also falls when the market is in equilibrium. With increased retention and a lower hiring rate, the overall workforce becomes more experienced and allocation of hours shifts away from new hires towards tenured staff.

Individual worker effect: Even without a change in retention behavior, labor-labor substitution can arise if firms change the number of hours that different types of employees work. For example, conditional on a fixed number of workers, full-time and overtime work amongst the most experienced workers could increase, while part-time work for less experienced workers and new hires could increase. Importantly, such a bifurcation in the hours distribution could result in a null average effect, indicating focusing on a single moment of the hours distribution might miss important dimensions of heterogeneity.

In practice, interactions between the retention and individual worker effects can occur. These interactions are especially likely if workers have strong preferences over certain schedules (such as part- or full-time, or the number of overtime hours). Importantly, however, worker preferences are likely heterogeneous across (unobservable) worker types, and we limit the analyses to the direct retention and individual worker effects in isolation. To the extent that these responses amplify each other, our short-term estimates will be a lower bound of the long-run responses.

3 Data and empirical framework

3.1 Minimum wages

Minimum wage increases occur frequently at the federal, state, county, and city level. In addition, some jurisdictions set different minimum wage rates for large and small employers. We match the staffing data to daily state, county, and city minimum wage rates for each employer size from Labor Center (2021). While the federal minimum remained unchanged during the October 2016 through December 2019 sample period, there was a substantial number of reforms at the state and local level. Overall, 68 state, 108 county, and 128 city-level reforms resulted in the majority of facilities experiencing at least one change over the period. The typical reform over this period was relatively modest at 62 cents, and the largest increase was $2.75 (Appendix Table A2).

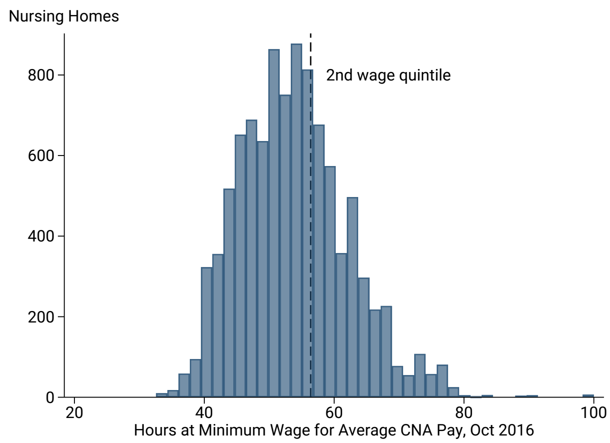
3.2 Low-pay labor markets with multiple employers

Nursing home labor markets Our study focuses on facilities operating in relatively unconcentrated labor markets. In order to identify these areas, we use residential and workplace Census data to construct a nursing home labor market concentration measure for each facility. We first use the Census Bureau LEHD Origin-Destination Employment Statistics (LODES) data to identify census blocks where nursing home employees live (Shen, 2020) and compute the distance between residence and workplace. We then compute a block-level labor market Herfindahl index (HHI) for each census block under the assumption that potential employers for each worker's residential block are within a 75th percentile commute (approximately 30km). We finally calculate the level of labor market concentration that facilities experience as the population-weighted average labor market HHI of the the blocks from which a facility's workers might reasonably commute. Additional details are provided in Appendix A.1. Our main results focus on facilities operating in a labor market with a concentration lower than 0.2, approximately the 80th percentile (Appendix Figure A4). As a representative example, a market with an HHI of 0.2 is one in which five identical facilities have an equal labor market share.

Low-pay areas Minimum wage increases are most likely to affect nursing home employees in places where the prevailing industry wage is close to the minimum. We identify these markets using wage data from the Quarterly Census on Employment and Wages (QCEW) and the Occupational Employment Statistics (OES). For each county c and quarter q, we compute the pay ratio of the average local CNA weekly wage to the local minimum wage, PR_{cq}, as a measure of how many hours a minimum wage worker would have to work in order to receive typical CNA pay:

$$PR_{ct} = \frac{\overline{CNAwage}_{ct}}{MW_{ct}}, \tag{1}$$

Figure 1: Pay Ratio Distribution



Note: Figure computed using QCEW average weekly earnings by county for 2016:Q4, statutory minimum wage information for each jurisdiction, and the ratio of CNA earnings to average industry pay from the May 2016 OES. Counties where the nursing home QCEW data are unavailable are aggregated to a "balance of state" jurisdiction, a weighted average of the weekly pay in the remaining counties within a state.

where $\overline{CNAwage}_{cq}$ is the average weekly wage for CNAs computed using the QCEW and OES data.[2] A low PR_{cq} indicates areas where CNAs earn wages close to the minimum. Figure 1 shows the full pay ratio distribution. We focus on facilities that are in areas in the bottom 40 percent of the CNA pay ratio distribution in the first quarter of each fiscal year. In this sample, nearly all representative workers – employees working 40 hours a week and receiving the typical pay for a CNA – are expected to be either directly or indirectly affected by a 15 percent increase in the minimum wage.[3]

3.3 Nursing home employment

The nursing home industry shares many characteristics with other low-pay industries. First, many nursing home staff receive low wages. We focus on certified nursing assistants (CNAs), which constitute the plurality of workers and typically earn low wages likely to be affected by minimum wage increases. For example, the median nursing assistant earned about $14 an hour in 2019, similar to retail industry wages (Bureau of Labor Statistics, 2020).

Second, like other low-wage occupations, turnover amongst CNAs is high, with annual turnover rates

[2]CNA-specific wages are not published at the county or facility level. We instead use average weekly earnings among nursing home workers for each county from the QCEW, scaled by the ratio of average CNA wages to the industry average from national OES data that year y as:

$$\overline{CNAwage}_{cq} = \underbrace{\overline{NHwage}_{cq}}_{\text{QCEW}} \underbrace{\frac{\overline{CNAWage}}{\overline{WageNH}}_{y}}_{\text{scaling factor, OES}} . \tag{2}$$

In areas where county-level average nursing home pay is suppressed, we calculate nursing home pay as the "balance-of-state" residual from state-level average wages minus counties with non-suppressed information (e.g.: balance of state counties).

[3]Existing work finds spillover effects accrue to higher-wage earners, with estimates ranging from about 120 percent or $3 above the new minimum (Cengiz et al., 2019; Dube et al., 2019; Gopalan et al., 2021).

exceeding 100 percent (Gandhi et al., 2021). These high turnover rates reflect an area of significant concern across the industry. For individual workers, high turnover leads to a lack of firm-specific knowledge and expertise, and can impede the performance of workers and caregiving teams. Beyond the direct implications for workers, high turnover creates significant operational challenges for facilities and are a key area of concern for healthcare regulators (Mukamel et al., 2009; Murrin, 2021). CMS considers high turnover to be a key indicator of poor quality, and began featuring turnover rates on its consumer-facing Nursing Home Compare tool and five-star rating system in 2022 (Centers for Medicare and Medicaid Services, 2022).

Our employment measures come from administrative shift-level microdata for the near-universe of employees and contract workers at U.S. nursing homes collected through the Payroll Based Journal (PBJ) program. These data include information on more than 700 million nursing shifts for 7.1 million employment relationships at more than 15,000 nursing homes covering the period October 2016 through September 2019. We do not extend our sample into 2020 because the COVID-19 pandemic dramatically impacted staffing in the industry (Shen et al., 2022).[4]

The richness of these administrative payroll data allows us to overcome several empirical challenges in the previous literature. First, the PBJ data precisely detail how many hours each employee worked each day in each occupation (nursing assistant, housekeeping, etc.), allowing us to track new hires, separations, occupational changes, and the allocation of hours and overtime shifts.

Second, facilities typically export their submission to CMS directly from time and attendance software in order to reduce errors and audit risk.[5] As a result, measurement error in hours worked is likely to be small. Importantly, this precision makes it unlikely that our estimates are attenuated due to measurement error. Empirically, we observe the hours associated with each shift with a high level of precision compared to measures from household surveys, such as those in the Current Population Survey. Figure 2 shows the full distribution of daily (panel A) and weekly (panel B) hours worked by CNAs who were paid an hourly wage in fiscal year 2019.[6] While there are spikes at standard half-hour lengths, like 7.5 and 8 hours, 58 percent of shifts do not end on a half-hour.[7] In contrast, approximately 50 percent of nursing assistants report working exactly 40 hours a week in the ACS and CPS data.

Figure 2 also illustrates a number of features of low-wage work in the nursing home industry. First, that there are a large number of employees who work considerably fewer than 40 hours per week. The data simultaneously indicates that there are a large number of employees working long shifts and overtime. More than a quarter of shifts are longer than 8 hours (7 percent are more than 12 hours), and 30 percent of employees work more than 40 hours each week. Accordingly, we are able to examine changes in hours worked across the entire hours distribution and how the allocation between part-time and full-time workers

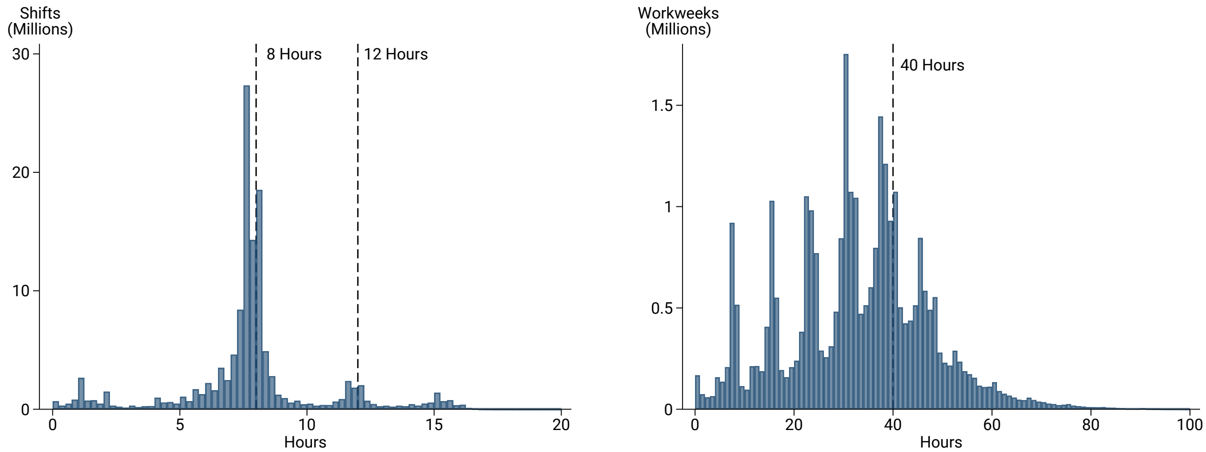
[4] Additionally, data for 2020Q1 are incomplete because CMS temporarily suspended the submission requirement to due to the extreme hardships facilities were facing.

[5] Many facilities even use additional software services, like SimplePBJ (formerly ezPBJ), to pre-audit submissions and spot potential errors.

[6] The federal fiscal year 2019 runs from October 1, 2018 through September 30, 2019.

[7] 7.5 hour shifts often represent an 8 hour shift with a 30 minute meal break. CMS requires facilities to exclude meal breaks, regardless of whether these breaks are paid. In contrast, household surveys round all responses to the nearest hour.

Figure 2: Hours Worked by Certified Nursing Assistants



(a) Daily Shifts **(b) Hours Worked Per Week**

Note: Figures computed using Payroll Based Journal data on CNA wage employees for fiscal year 2019.

changes.

Table 1: Summary Statistics

	New Hires		Tercile 1		Tercile 2		Tercile 3	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Fiscal Year 2018 (3,183 Facilities)								
Hours Per Bed	3.05	2.67	1.91	1.56	3.22	2.30	4.86	3.09
Number of Workers Per Bed	0.10	0.09	0.07	0.06	0.11	0.08	0.13	0.08
Overtime Hours Per Bed	0.19	0.29	0.10	0.16	0.16	0.24	0.43	0.45
Share of Full-Time Workers	0.32	0.22	0.21	0.18	0.29	0.19	0.55	0.20
Share of Workers with Overtime Hours	0.21	0.21	0.14	0.17	0.19	0.18	0.38	0.22
Tenure Range (Hours at Start of Fiscal Year)	[0, 0]		(0, 599]		(599, 1522]		(1522, 4957]	
Panel B: Fiscal Year 2019 (3,430 Facilities)								
Hours Per Bed	2.87	2.82	2.10	1.84	3.11	2.06	4.99	3.13
Number of Workers Per Bed	0.10	0.10	0.08	0.07	0.11	0.07	0.14	0.08
Overtime Hours Per Bed	0.18	0.27	0.13	0.20	0.20	0.26	0.46	0.49
Share of Full-Time Workers	0.33	0.23	0.24	0.19	0.31	0.19	0.52	0.19
Share of Workers with Overtime Hours	0.22	0.22	0.17	0.19	0.22	0.19	0.36	0.22
Tenure Range (Hours at Start of Fiscal Year)	[0, 0]		(0, 761]		(761, 2616]		(2616, 9297]	

Notes. Data from PBJ fiscal year 2018 and 2019. Sample restricted to facilities in labor markets with an HHI less than 0.2 and in the bottom two quintiles of the nursing assistant pay distribution for each fiscal year. Tenure terciles based on the national distribution of firm-specific hours for each fiscal year. Hours per bed, overtime hours per bed, and number of workers per bed include all facility-weeks, including those with zero hours or workers. Share of full-time workers and share of workers with overtime hours only include facility-weeks with reported hours.

Finally, we leverage the individual-level nature of the PBJ data to track how higher minimum wages affect different types of workers. We measure each worker's experience level in each fiscal year based on the total number of firm-specific hours accrued prior to the start of the fiscal year. Because we cannot track workers across facilities, this measure of experience is most accurately conceptualized as a worker's "tenure," since some workers with low tenure at a given facility may have substantial prior experience at other facilities. For ease of exposition, we use experience and tenure interchangeably to signify firm-specific experience. We discretely categorize workers' level of experience in each fiscal year based on which tercile of national distribution of tenure they fall in at the start of the fiscal year. As our data begin in fiscal year 2017, we exclude this first fiscal year from the experience analyses. Table 1 shows in our main analysis sample, the least experienced workers work fewer hours and fewer overtime hours than their more experienced co-workers in each fiscal year. In total, nursing assistants provide about 13 hours of care per bed each week across all experience groups.

3.4 Other data

We supplement the PBJ data with information from several sources in order to control for conditions and policies that may be correlated with both minimum wage changes and employment outcomes. We control for economic conditions with monthly county unemployment rates from the BLS Local Area Unemployment Statistics (LAUS) program, for other policies targeted to low-income populations using the University of Kentucky National Welfare Data, and for nursing home resident and facility characteristics using data from Brown University's Long Term Care Focus (LTCFocus) database. In ongoing work, we are incorporating other information on other nursing home regulations, including whether a facility is in a state with a minimum staffing requirement or with a cost-based Medicaid formula.

3.5 Empirical approach

Short-term TWFE analyses: We estimate changes in employment levels and composition resulting from changes to the minimum wage at the facility-level. Following much of the existing literature, we estimate the following two-way fixed effects (TWFE) regression for each outcome Y in facility f during week t:

$$Y_{f,t} = \beta MW_{f,t} + X^{'}_{f,t}\phi + \gamma_{f,y(t)} + \eta_t + \varepsilon_{f,t}, \tag{3}$$

where $y(t)$ is the fiscal year (October 1 through September 30) for week t.

In this framework, the coefficient of interest, β, represents the expected change in outcome Y resulting from a \$1 increase in the minimum wage. For each outcome, we also report representative elasticities, which are the implied elasticities evaluated at the average minimum wage and outcome. The term $\gamma_{f,y}$ is a facility-fiscal-year fixed effect. In allowing our facility fixed effects to vary across fiscal years, we account for medium-term changes in employment patterns and economic conditions that may vary within a facility over time. In addition, by identifying the effect of minimum wage changes within a single fiscal year, this approach mitigates issues arising with negative weighting that can arise in TWFE models when treatment occurs at different times (de Chaisemartin and d'Haultfoeuille, 2019; Callaway and Sant'Anna, 2020).[8] Week fixed effects, η_t, account for general economic trends and seasonal patterns that pertain to all facilities. $X_{f,t}$ is a vector of time-varying controls that might be correlated with minimum wage levels or nursing

[8]Appendix tables include specifications with separate facility and fiscal year fixed effects γ_f and κ_y. This approach is most similar to the previous literature, but is more prone to issues of negative weighting with repeated and staggered treatments which may bias the estimates.

home employment. Out main specification includes only overall county unemployment rate. We cluster all standard errors at the county level since the county is the modal level of treatment over our analysis period.

Event study analyses: Since hiring, training, and retention decisions do not all occur instantaneously, the short-term effects of higher minimum wages might differ from longer-term responses. If responses cumulate over multiple periods, the TWFE estimate will understate the longer-term effect (Goodman-Bacon, 2021). In addition, minimum wage policies are announced several months before the implementation date. If firms change hiring and staffing practices before the effective date in anticipation of a higher future wage, the TWFE approach will again understate the full effect.

In order to shed light on the timing of these responses, including anticipation effects and medium-term shifts, we leverage an event study framework. The event study extension estimates different treatment effects for different event-times relative to the minimum wage change. For each treated facility f in a given fiscal year, we denote the event-time for facility f on week t in that fiscal year by $\tau(f,t)$. τ is the number of weeks relative to the minimum wage implementation date affecting facility f in fiscal year $y(t)$. To allow treatment effects to scale with the size of a minimum wage change, we scale our event-time indicators by the size of the minimum wage change facility f experiences that fiscal year (Finkelstein et al., 2016; Ruffini, 2020), denoted as $\Delta^{MW}_{f,y(t)}$. The event-study framework therefore takes the form:

$$Y_{f,t} = \beta_{\tau(f,t)}\Delta^{MW}_{f,y(t)} + X^{'}_{f,t}\phi + \gamma_{f,y(t)} + \eta_t + \varepsilon_{f,t}. \tag{4}$$

For clarity and ease of interpretation, we restrict the treated sample in the event study analyses to include only the approximately 70 percent of reforms that involve a single minimum wage change occurring the first week of January. This restriction excludes, for example, reforms that are phased in over several months or that include increases in January and July. It also excludes facilities that experienced a minimum wage increase on a date other than January 1. One advantage to this approach, however, is that we have a balanced event time panel for each fiscal year, which allows analyses over a longer period. Specifically, as the event times $\tau \in \{-13, -12, \ldots 38, 39\}$ correspond exactly to weeks in the fiscal year (October 1 through September 30) relative to January 1st, the event studies trace out the effect of minimum wages over the quarter prior to the minimum wage change at start of the calendar year through the three quarters after the change.

4 The Effect of Minimum Wages in Competitive Labor Markets

4.1 Effect on Employment Levels

Relatively little is known about how minimum wages affect healthcare support staff in the US context, despite the prevalence of low wages in this sector. Table 2 broadens our understanding of how minimum wages operate by showing how higher minimum wages affect nursing home employment, measured by hours and number of workers in each occupation and pay type.

Panel A shows that a \$1 increase in the minimum wage increases the amount of time worked by CNAs earning an hourly wage by about 10 minutes per bed per week. While point estimates suggest a slight decrease in the hours worked by CNAs who are employed through a contract agency, this estimate is not statistically significant. Higher minimum wages also prompt firms to increase their use of LPNs—credentialed staff who are the closest substitute to CNAs. In contrast, there is no evidence of substitution towards higher-skilled labor that are weaker substitutes for CNAs, namely RNs. Panel B also shows no significant disemployment effect on the extensive margin, defined as the number of workers in a given occupations; rather, the number of CNAs and LPNs increases.

Finally, minimum wage increases do not substantively change occupancy rates. Thus, the effects we measure represent changes in the quantity and composition of inputs (workers) rather than the quantity of output (bed days provided). Particularly in the nursing home context, we can interpret these input changes as yielding changes in the quality of care patients receive.

The 2016-2019 period differs from previous eras of minimum wage reforms as the recent period only includes state and local changes, many of which are annual changes that account for increases in the cost of living. In contrast, throughout much of the 1990s and 2000s, minimum wage increases occurred due to legislative action at the federal or state level and were much more punctuated occurrences. Despite these differences in the nature of minimum wage changes over time, the patterns we find for the 2016-2019 period are similar to those found in the nursing home industry for the period spanning the 1990s through 2017 (Ruffini, 2020). That we find similar changes in employment in both periods suggests that the type and frequency of minimum wage reforms does not substantially influence firms' responses in this sector.

Beyond the healthcare industry, there is less agreement about the size of the employment response for the broader minimum wage workforce, but estimates center around zero (Doucouliagos and Stanley, 2009). Many of these estimates, however, are based on self-reported hours from household surveys and are sufficiently imprecise so as not to rule out sizeable increases or decreases in employment. Accordingly, attenuation bias stemming from measurement error in reported hours worked is a first-order concern in much of the existing literature. The estimates in Table 2 improve upon much of this work by relying on administrative payroll data that reports daily hours with a high degree of precision and is subject to audit, making measurement error is less of a concern in this setting. We can reject any disemployment effect among lower-wage workers (CNAs and LPNs) with 95 percent confidence and find that any reductions in nursing home employment are due to lower reliance on workers hired through contract agencies.

The patterns in Table 2, as well as much of the existing minimum wage literature, can arise in labor markets with search frictions or employer bargaining power (Manning, 2013). Even without such frictions, employers in competitive labor markets could respond to higher minimum wages by reducing other costs (including other forms of compensation) rather than lowering employment levels (Clemens, 2021). In the subsequent analyses, we examine some of these additional margins, focusing on CNAs paid an hourly wage,

Table 2: Hours and Number of Employees per Bed, by Occupation and Pay Type

	CNA Positions			Other Nursing Staff		Occupancy Rate
	Wage	Contract	Salaried	LPN	RN	
Panel A: Weekly Hours per Bed						
Minimum Wage	0.162	-0.023	0.011	0.062	-0.008	0.002
	(0.076)	(0.015)	(0.011)	(0.034)	(0.025)	(0.001)
Mean	13.06	0.35	0.07	4.68	2.84	0.82
Std. Dev.	4.21	1.10	0.88	2.39	2.54	0.15
Implied Representative Elasticity	0.123	-0.645	1.562	0.131	-0.028	0.019
Panel B: Weekly Payroll per Bed						
Minimum Wage	0.005	-0.001	0.000	0.001	0.001	
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	
Mean	0.51	0.04	0.00	0.17	0.12	
Std. Dev.	0.21	0.12	0.04	0.10	0.20	
Implied Representative Elasticity	0.097	-0.178	0.155	0.080	0.053	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility × FY	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	673	673	673	673	673	673
Facilities	3,907	3,907	3,907	3,907	3,907	3,907
Facility-Weeks	342,657	342,657	342,657	342,657	342,657	342,657

Notes. Table shows weekly hours per bed (panel A) and number of workers per bed (panel B) for fiscal years 2017 through 2019. All specifications include week and facility-by-fiscal year fixed effects and control for the county unemployment rate. Standard errors clustered by county in parentheses.

as this group is most likely experience an increase in hourly pay when the statutory minimum wage increases (Ruffini, 2020).

4.2 Effect on Hours Allocation by Worker Experience

Although we do not observe large changes in the aggregate amount of CNA labor, the results in Table 2 may miss shifts across different types of workers within an occupation. Employees differ on a multitude of types, some of which are unobservable in our setting — such as productivity or educational attainment — and others that are observable — such as firm-specific human capital.

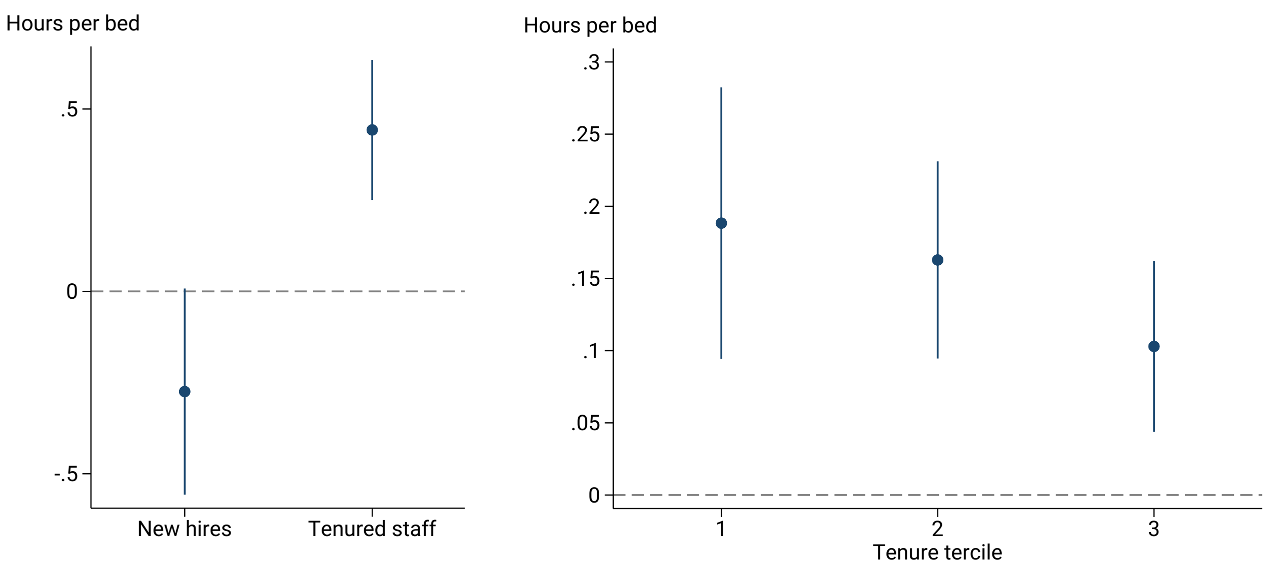
Firm-specific experience is a key dimension of interest in the nursing home industry for both theoretical and practical reasons. First, high turnover results in high recruitment and training costs, so greater retention can benefit both workers and firms (Becker, 1962; Hashimoto, 1981). In the context of the nursing home sector, high turnover is associated with lower quality of care (Gandhi et al., 2021). Second, differences in employment by experience raise distributional considerations as wages generally increase with experience (Mincer, 1991). Therefore, any additional recruitment due to higher minimum wages is expected to amplify the mechanical effect of higher minimum wages on bottom-tail inequality. Conversely, shifts towards more experienced workers diminish any reductions in inequality.

We first compare hours worked between new hires and tenured workers, where "tenured" includes all employees who began to work for their current employer before October 1 of the fiscal year and "non-tenured" are employees who began work after October 1st. We then then divide tenured workers into terciles based on the number of hours the employee had worked at the facility before the start of the fiscal year.[9]

Figure 3 indicates the aggregate results in Table 2 mask heterogeneity between new workers and those with some firm-specific experience: higher minimum wages lead firms to shift the allocation of hours away from new hires and towards more experienced workers (panel A). Looking across terciles in panel B, these additional hours are somewhat smaller for the most experienced workers and larger for workers in the first two terciles.

Figure 3: Hours per Bed, CNAs by Tenure

(a) **(b)**



Notes. Figure shows weekly hours per bed for fiscal years 2018 through 2019 by new hires and workers employed at the start of the fiscal year. Tenure terciles are based on the national experience distribution for each fiscal year. All specifications include week and facility-by-fiscal year fixed effects and control for the county unemployment rate. Vertical bars denote 95% confidence intervals with standard errors clustered by county.

The shift in hours allocation towards tenured workers in the nursing home sector is consistent with recent case studies that explore a single local minimum wage change. For example, Jardim et al. (2020) find that earnings for incumbent workers increase after Seattle's minimum wage increase, but less-experienced workers were likely to lose employment. Gopalan et al. (2021) also find no disemployment effects among incumbent workers who were earning wages slightly above the new minimum.

The results in Figure 3 show the short-term change in the allocation of hours averaged up to nine months after a higher wage becomes effective.[10] Figure 4 extends the approach in Figure 3 to an event study

[9] Terciles are defined based on the national distribution for each fiscal year Workers in the 1st tercile had worked up to 599 (761) hours with their employer in fiscal year 2018 (2019); workers in the second tercile had worked up to 1,522 (2,616); and workers in the third tercile up to 4,957 (9,297) (Table 1).

[10] The facility-by-fiscal year fixed effects limits comparisons to the October-September period; in our sample, the first minimum wage changes in each fiscal year occur on January 1. Appendix results that include facility and fiscal year effects separately

framework (Equation 4) in order to provide insights on how quickly employers adjust workplace schedules in response to an increase in the statutory minimum wage and whether these changes begin before the higher wage becomes effective.

Figure 4 shows two key patterns. First, the amount of hours worked by new hires is lower in areas that experienced an increase in the minimum wage than in areas that did not experience a wage increase (panel A). The flatter slope in the weeks leading up to the reform suggests some anticipation effect among firms that became subject to a higher minimum in January, and the use of new hires continues to grow relatively slower over the following 9 months among these firms.

Second, panels B-D show a reverse pattern for each tercile of tenured workers: Prior to the minimum wage increase, workers in each tercile of the tenure distribution did not work more hours than their counterparts in non-minimum wage areas. After the higher wage becomes effective, there is an immediate, short-term increase in the number of hours worked by tenured staff in the first ten weeks of the higher wage. The increase in hours among tenured workers persists for at least 9 months. This change is smaller among most experienced workers, most of whom worked full-time schedules before the minimum wage increase.

Figure 5 stacks all of the event study results in Figure 4 to illustrate how the total number of hours and the share of hours worked by workers with different experience levels differs between areas that did not and did experience an increase in the minimum wage. We scale the effects so that Figure 5 illustrates the estimated effect of a \$3 increase in the statutory minimum wage. While a \$3 is large compared to minimum wage increases over our sample period —the average increase in our sample is \$0.62—it is small compared to some current minimum wage proposals, as well as other historical changes (in percentage terms). For example, in 2019, moving to a \$15 minimum wage would entail an increase of about \$5 for the median facility in our sample.

As foreshadowed by Table 2 and Figures 3 and 4, higher minimum wages do not depress overall employment, but such changes so shift the share of hours away from new hires to tenured employees. Nine months after the minimum wage increases, the share of hours worked by new hires is 56.52 percent (13.37 percentage points) lower than it would have been without the wage increase.

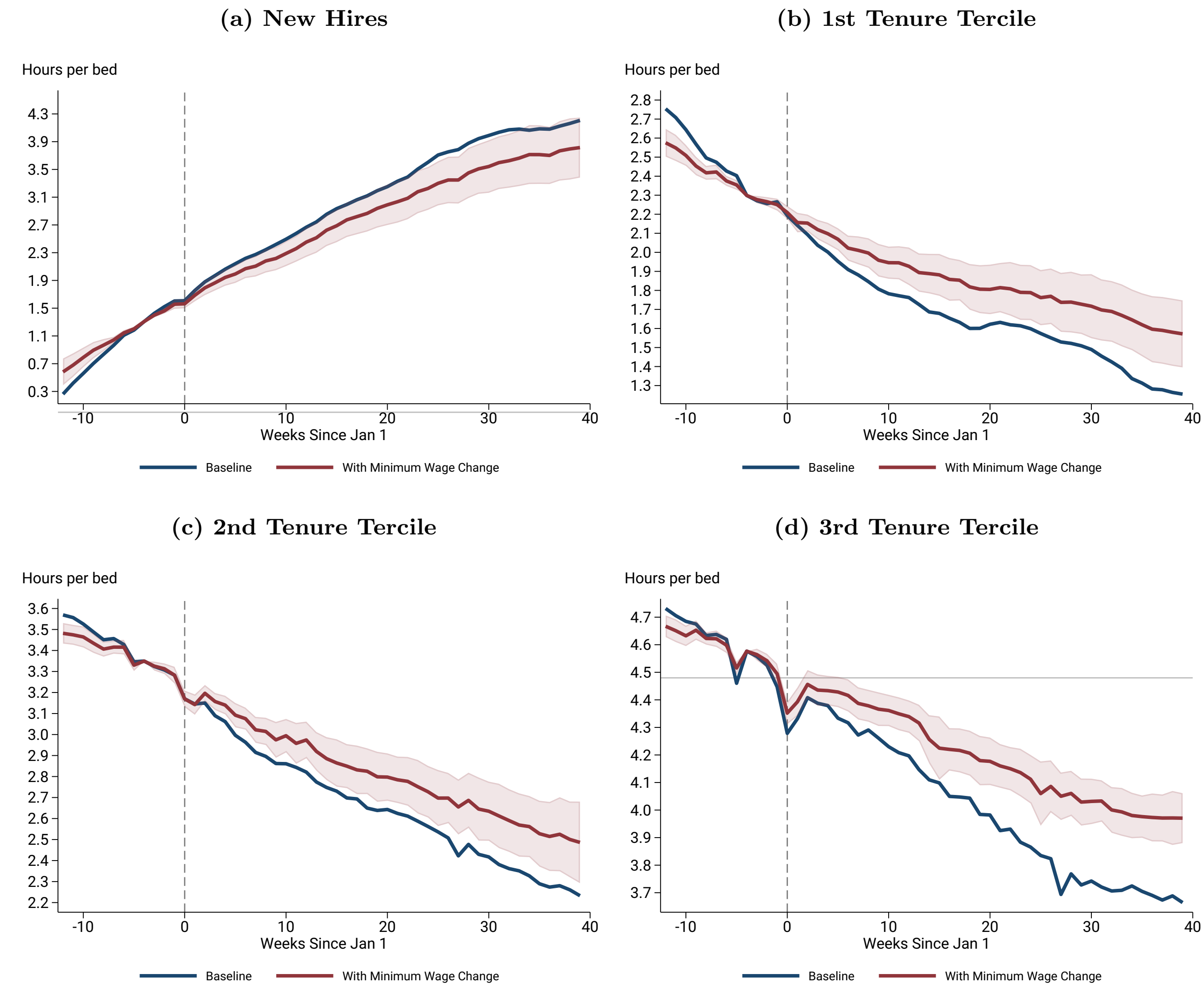
4.3 Decomposing the Composition Effect

The shift in the allocation of hours towards tenured workers could occur due to responses on the extensive or intensive margin, or a combination of the two. First, higher minimum wages could change worker retention, and therefore the number of both tenured workers and new hires necessary to replace those who separate. Second, changes in the new hire-versus-tenured wage gap could lead firms to adjust the number of hours worked by individual workers.

This section decomposes the overall allocation into the retention effect and the individual-worker effect. Whereas the previous section focused on the allocation of hours at the *firm* level, the following section

report slightly longer effects that are averaged up to 2.5 years after an increase.

Figure 4: Dynamic Effects of Minimum Wages on Hours Worked



Notes. Figure shows weekly hours per bed for fiscal years 2018 through 2019 by new hires and workers employed at the start of the fiscal year. Tenure terciles are based on the national experience distribution for each fiscal year. All specifications include week and facility-by-fiscal year fixed effects and control for the county unemployment rate. Shaded area denotes 95% confidence intervals with standard errors clustered by county.

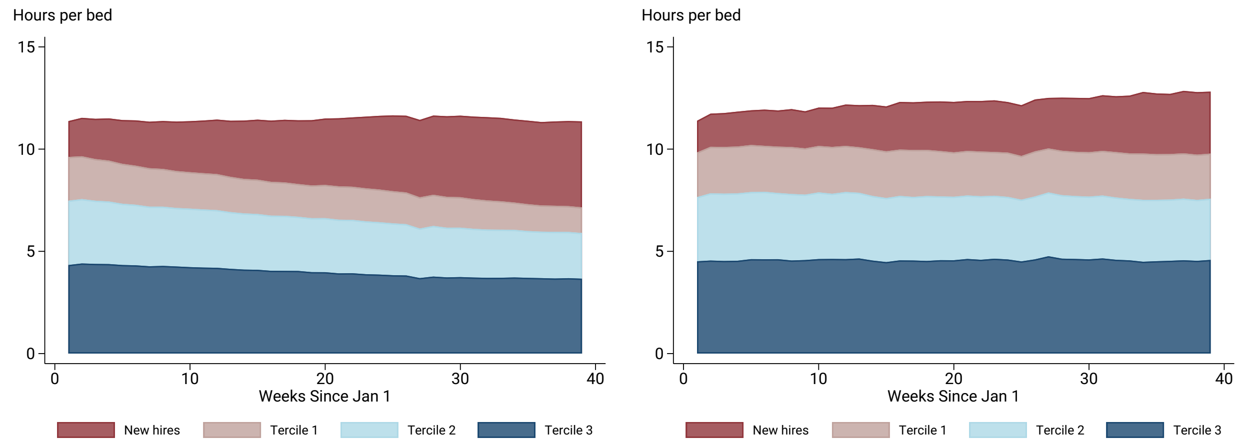
examines effects at the *worker* level. There is substantial variation in the tenure composition across firms: some firms rely more on new hires and others on experienced workers. Therefore, the firm, and worker-level approaches present two complementary analyses for understanding how minimum wages affect low-pay labor markets.

4.3.1 Changes in Worker Retention

In other low-wage labor markets, increases in the minimum wage reduce worker flows by lowering the hiring and separation rates (Dube et al., 2016; Portugal and Cardoso, 2006). These patterns are broadly consistent with job ladder models in which higher minimum wages reduce the arrival rate of better paying jobs, but largely describe aggregate patterns without distinguishing across workers with varying amounts of experience

Figure 5: Overall Change in Hours Worked, by Tenure

(a) No Minimum Wage **(b) Minimum Wage, Jan 2018 or Jan 2019**



Notes. Figure shows weekly hours per bed for fiscal years 2018 through 2019 by new hires and workers employed at the start of the calendar year. Tenure terciles are based on the national experience distribution for each fiscal year. The stacked curves display the effect of a \$3 increase in the minimum wage based on Figure 4. Panel A shows facilities without a minimum wage increase; panel B shows facilities with a minimum wage increase.

(and therefore, initial wages).

Table 3 first shows that a \$1 increase in the minimum wage does not significantly change the hiring rate for wage CNAs, but reduces the separation rate falls by 0.055 percentage points. The magnitude of the drop in the separation rate is similar to responses found in other low-wage settings, including among food service workers (Dube et al., 2016) and teenagers (Portugal and Cardoso, 2006).

The remaining columns of Table 3 provide some of the first evidence on whether the reduction in separations following higher minimum wages is due to retention among workers with more or less firm-specific experience. Changes in worker turnover differ depending on worker tenure with the facility: the newest hires are more likely to leave their firm, whereas workers with extensive firm-specific experience – those in the top two experience terciles – become significantly more likely to continue employment.

Lower separations could arise from employee or employer decisions or a combination of the two. We are unable to distinguish between voluntary and involuntary separations, and both are theoretically plausible. First, from the workers' perspective, higher minimum wages reduce pay differentials at the bottom of the income distribution. In areas with frictional wage inequality, such compression reduces the arrival rate of higher-paying jobs and job-to-job transitions. Second, with unknown worker productivity at hiring, higher minimum wages can reduce firms' asset value of a vacancy if new hires are paid the minimum wage during a "probationary period" in which employers learn about a worker's productivity (Brochu and Green, 2013). However, firms know the productivity of their incumbent workers and the probationary costs are sunk for these workers. Under this framework, if the most experienced workers have the highest firm-specific productivity values, reductions in the separation rate should be weakly increasing in firm-specific experience.

More broadly, other work has found that higher minimum wages lead firms to hire more productive

Table 3: Worker Flows - Hires/Separations Rates

	New Hires (% of payroll)	Separations (% of payroll)				
		All	New Hires	Tercile 1	Tercile 2	Tercile 3
Minimum Wage	0.018	-0.055	0.377	-0.048	-0.106	-0.108
	(0.078)	(0.033)	(0.132)	(0.066)	(0.026)	(0.023)
Mean	1.62	1.62	4.25	1.62	1.00	0.54
Std. Dev.	7.57	3.34	11.07	5.88	4.37	3.82
Implied Representative Elasticity	0.107	-0.336	0.877	-0.291	-1.047	-1.985
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility × FY	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	673	673	673	673	673	666
Facilities	3,907	3,907	3,907	3,907	3,907	3,907
Facility-Weeks	342,657	342,657	342,657	342,657	342,657	342,657

Notes. Table shows weekly hiring or separation rate for fiscal years 2018 through 2019. Tenure terciles are based on the national experience distribution for each fiscal year. Numerator is the number of workers who began or ended employment in week t; denominator is the number of workers employed in the previous week, $t-1$. All specifications include week and facility-by-fiscal year fixed effects and control for the county unemployment rate. Standard errors clustered by county in parentheses.

workers (Butschek, 2022) and increase the formal education requirements in job postings (Clemens, 2021). The results in Table 3 indicate that higher minimums also enable firms to retain workers with the highest levels of firm-specific human capital – those that are likely to have relatively high productivity.

4.3.2 Changes in Individual Hours

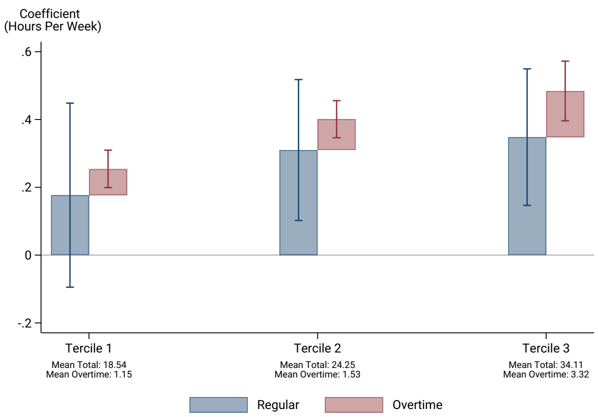
In addition to greater numbers of high-experience workers, a greater share of total facility hours worked by experienced CNAs could arise if each individual worker works additional hours after the minimum wage increases. As shown in Figure 2, there is wide variation in the number of hours nursing assistants work in a week: approximately one third of workers work part-time and another one-third work more than 40 hours a week. Accordingly, the hours distribution at points that are not fully captured by average hours.

Changes in regular and overtime hours Each panel of Figure 6 looks a different component of hours worked among individual workers. Panel A shows that experienced workers are working more regular hours and overtime hours after the higher minimum wage, and both types of hours are increasing in worker experience levels. Accordingly, although the bite of the minimum wage is more pronounced for new hires, workers who have been with their firm for relatively long periods also receive income benefits through increases in their hours and overtime. To our knowledge, this is the first analysis of how increases in the minimum wage change the use of overtime. That firms do not reallocate hours among workers to minimize the use of overtime presents somewhat of a puzzle from the perspective of a profit-maximizing firm, as overtime is paid at 1.5 times the worker's usual wage. However, such responses could occur if firms experience staffing shortages and higher minimum wages increase the value of working overtime beyond a worker's reservation wage.

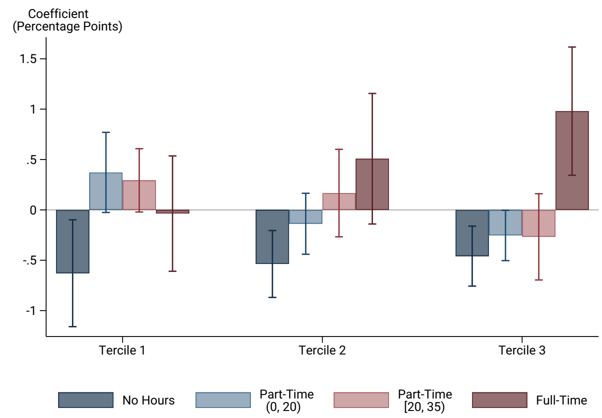
Changes in part-time and full-time work Panel B considers other points of the hours distribution and indicates that workers with relatively low levels of experience become more likely to work part-time (fewer than 35 hours a week), whereas more experienced workers are increasingly working full-time. All categories of experienced workers become less likely to have a week with no hours worked. While we are unable to discern voluntary vacations from forced leave, less extended time away from work is consistent with higher minimum wages promoting greater attachment to the workforce by increasing the opportunity cost of leisure.

Figure 6: Characteristics of Low-Wage Work

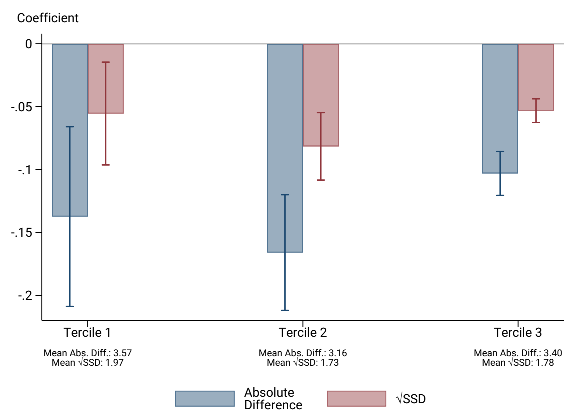
(a) Hours Per Worker



(b) Part-Time and Full-Time



(c) Scheduling Volatility



Notes. Figure shows the change in weekly hours (panel A), likelihood of working part- or full-time (B), and scheduling volatility (C) among CNAs paid an hourly rate in fiscal years 2018 and 2019. Tenure terciles are based on the national experience distribution for each fiscal year. All specifications include week and individual-by-fiscal year fixed effects and control for the county unemployment rate. Vertical bars show 95% confidence intervals with standard errors clustered by county.

Changes in scheduling volatility An additional dimension of job quality that has not been extensively studied in the existing literature is scheduling volatility, or whether workers work a stable combination of days and hours from one week to the next. Whether weekly variation in hours worked is a job asset or disamenity may vary with worker preferences and characteristics. On one hand, scheduling volatility may reflect greater scheduling flexibility that allows employees to increase or decrease hours to reflect their consumption demands and non-workplace obligations. On the other hand, variation in the number of hours worked from one week to the next increases variation in weekly pay, increasing the difficulty of budgeting and meeting expenses, particularly for workers with little savings.

Two measures in panel C provide insights on scheduling and hours volatility. First, "Absolute Difference" measures absolute difference in week-over-week total hours and captures how much earnings volatility workers might expect across paychecks. Second, $\sqrt{SSD}$ is defined as the sum of squared deviations of hours worked each day of the week, normalized by total hours worked. This measure incorporates both volatility in the total number and how these hours are allocated across days, providing a measure of general uncertainty, such as difficulties in planning for transportation, child care or other activities.

Figure 6 Panel C illustrates that new hires' schedules become less volatile after the minimum wage rises across both volatility measures and all experience categories. That schedules become more stable suggests a possible mechanism for increased retention. One such explanation is that scheduling volatility increases income volatility, and can increase material hardship, in turn, leading to high turnover (Schneider and Harknett, 2019, 2021). Empirically, Bergman et al. (2021) find that increased volatility among home health nurses due to co-worker absences increases separations. Our findings consider the opposite case: higher wages reduce material hardship, while reductions in scheduling volatility reduce uncertainty, leading to greater retention. These patterns can also produce a positive feedback loop, whereby greater retention or fewer missed shifts among co-workers reduces other workers' scheduling uncertainty and can increase these workers' retention as well.

Altogether, the patterns in Figure 6 are consistent with responses to minimum wages documented in other settings. For example, Jardim et al. (2020) find that the 2013-15 Seattle minimum wage increases increased hours of incumbent workers at the expense of new hires and Gopalan et al. (2021) find minimum wage increases did not decrease hours of incumbent workers across the U.S. In combination with our results, these studies suggest that applying the mechanical increase in hourly wages overstates any reduction in inequality at the bottom tail of the income distribution.

The positive correlation between additional hours worked and worker experience raises distributional considerations. While higher minimum wages reduce lower tail *wage* inequality (Lee, 1999; Cengiz et al., 2019), this compression is partially undone when considering the total effect on *earnings*. Based on industry-level wage profile data from Payscale.com and the earnings elasticities in Ruffini (2020), that the most experienced workers receive the most additional hours after an increase in the minimum wage attenuates the mechanical reduction in wage inequality between the first and third tenure tercile by about 40 percent.

4.3.3 Quantifying the Retention and Individual Responses

Figure 7 combines the results from Sections 4.3.1 and 4.3.2 in an event study framework to examine the relative contributions of the retention and individual effect to the overall allocation of hours for workers in each experience tercile. The left panel shows the combined retention and individual effect – that is, each employee's hours are set to 0 after he or she separates. The right panel isolates the individual worker effect where each employee is dropped from the sample after he or she separates. We then aggregate all hours into experience bins and divide by the number of workers.

Figure 7 panels A-B show no significant change in hours per worker for relatively inexperienced workers. For more experienced workers, panels C-F illustrate that both the retention and individual worker effects play a role, but whereas the retention effect grows over time, the individual effect is a one-time increase that arises approximately one month after the higher wage becomes effective. More precisely, three months after the wage increase, the retention and individual worker effects account each account for about 50 percent of the hours allocation shift for workers in the second and third quintile. The retention effect grows in relative magnitude over time that by the end of the ninth month, the retention effect accounts for about two-thirds of the overall shift.

4.4 Simulating the Long-Run Impact of Increasing the Minimum Wage

Our reduced-form estimates capture the effect of minimum wage increases within a given fiscal year, or up to nine months after the higher wage becomes effective. Our estimates indicate that facilities experiencing an increase in the minimum wage improve retention of tenured staff and slow hiring of new staff. Since minimum wage increases are typically permanent, the higher retention and reduced hiring are likely to continue even after the end of the fiscal year and further accumulate over time. Correspondingly, the facility's distribution of staff tenure will continue to increase each year until it reaches a new equilibrium.

In this section, we simulate these potential *long-run* impacts of minimum wage increases. There are two primary channels through which we expect effects to accumulate over the long-run. The first is that the estimated change in hiring rates, retention rates, and hours allocations for each tenure tercile are likely to persist into future fiscal years. The second is that as the composition of staff becomes more tenured, ongoing employee retention will further increase even absent further minimum wage changes because retention rates among high-tenure staff are much higher than the retention rate for newer workers.

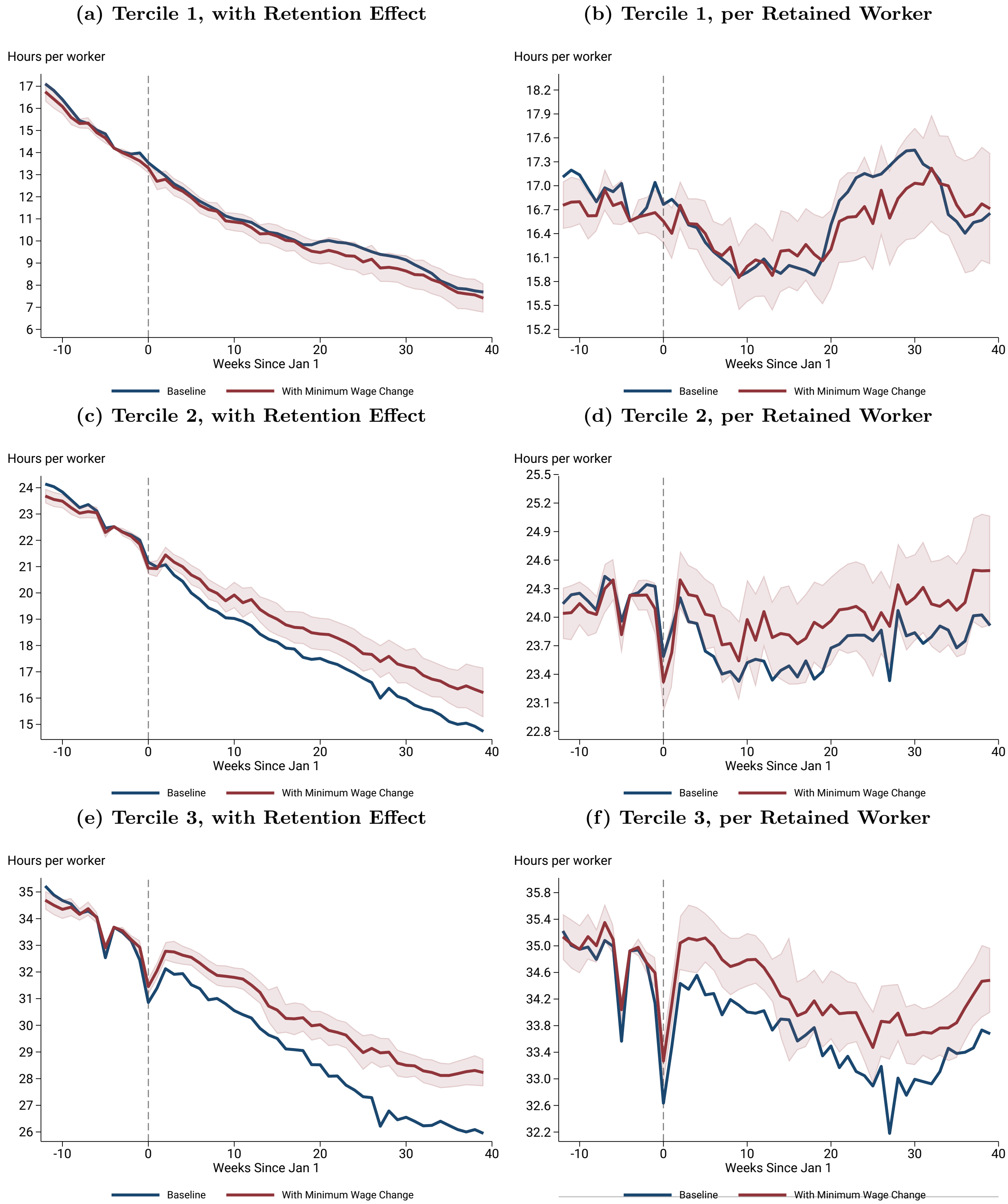
Our simulation leverages the reduced-form estimates to depict the evolution of employment composition after a $1 increase in the minimum wage from an initial equilibrium toward a new equilibrium distribution. To do this, we iteratively simulate on a weekly basis which staff are retained, whether any new staff are hired, and how hours are allocated to each staff member. We summarize our approach here and provide additional details in Appendix A.7.

We simulate each employee's retention each week from a Bernoulli distribution with the retention probability based on the fiscal week and the employee's tenure category. We then apply average retention among facilities without a minimum wage increase (blue lines) to fiscal years prior to the minimum wage increase and the estimated treatment effects (red lines) for fiscal years including and after the increase.[11]

Next, we simulate hiring rates under the assumption that facilities maintain the levels of patient care

[11] Appendix A.7 describes the process for calculating retention rates of new hires.

Figure 7: Changes in Hours per Worker, With and Without Changes in Retention



Notes. Figure shows the change in weekly hours per worker by experience tercile for fiscal years 2018 and 2019. Panels A, C, and E include the retention and individual effect by including all workers who were employed at the start of the fiscal year and setting individual hours equal to zero after an employee leaves. Panels B, D, and F isolate the individual worker effect by dropping workers after they separate. Blue line shows average hours per worker for facilities that did not experience a minimum wage increase during the fiscal year. Shaded area shows 95% confidence intervals with standard errors clustered by county.

(hours per bed) based on our estimates. We use a Poisson process to model the hiring by each facility, where the arrival rate of new hires adjusts weekly in expectation for the immediate deficit in the total hours of care per bed as estimated in Figure A24. We thus address the dynamics of facilities' hiring behavior in response to the weekly changes in workers' retention and hours allocations in order to avoid overestimating the hiring rate at facilities where the tenure composition becomes more experienced over time.

Finally, we draw weekly shifts for each worker from the empirical shift distribution at facilities without a minimum wage increase.[12] When simulating fiscal years before the minimum wage increase, we use these estimates directly. For fiscal years during and after the minimum wage increase, we adjust the weekly hours allocations according to the event study estimates for each week t (Figure 7). For workers still on payroll at the end of the fiscal year, we determine their tenure bin for the following year based on their total hours worked up to that point in the simulation. Thus, as workers become more tenured, we apply estimates applicable to their cumulative tenure at the start of each fiscal year.

We base the initial equilibrium employment composition on the set of control facilities for fiscal year 2019 by applying the simulation method to control facilities and their employees until the employee composition reaches an equilibrium (up to seasonal variation).[13] From this initial equilibrium, we compare the simulation progresses with and without a \$1 increase in the minimum wage. We run these simulations week-by-week until the employment composition under the \$1 increase in the minimum wage reaches a new equilibrium.

Figure 8 presents the simulated impact of increasing the minimum wage by \$1. Panel 8a shows the initial equilibrium hours-weighted tenure distribution at the start of the fiscal year during which the \$1 increase will be implemented. This represents the tenure composition of employee hours—or equivalently, the tenure composition of care that residents receive—prior to the minimum wage increase. Panel 8b depicts how this distribution shifts three quarters after the change occurs and suggests a slight increase in the number of hours coming from high-tenure CNAs with the average and median hour of care increasing by 240 and 293 tenure hours, respectively.

Panel 8c shows a more pronounced long-run effect of a \$1 minimum wage increase. At the new equilibrium, the hours-weighted average and median tenure of care are 1949 (38%) and 1454 (55%) hours higher. The share of patient care hours received from workers with more than 2,000 hours of firm-specific experience (approximately equivalent to one year of full-time employment) also increased by 8 percentage points from the baseline of 57%. This shift represents a dramatic shift in the composition of workers and correspondingly in the level of tenure of the staff from which residents receive care. This result indicates that minimum wages are a more effective tool to reduce nursing staff turnover and increase tenure in the long-run than in the short-term.

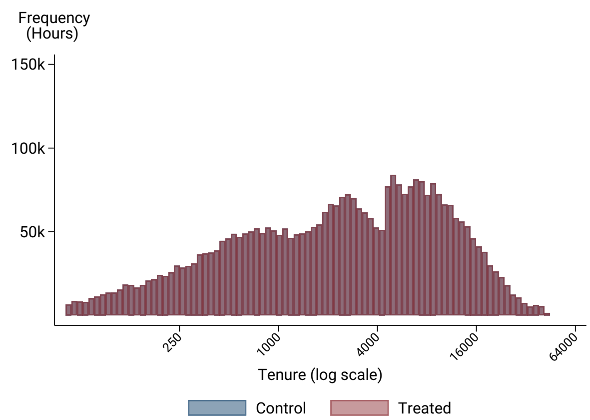
This simulation assumes that facilities' retention rates for staff at different levels of tenure will remain

[12] We draw each simulated worker's full set of weekly shifts in a fiscal year from the empirical distribution of workers at control facilities in the same tenure tercile as the simulated worker and with the same first and last day on payroll in the fiscal year.

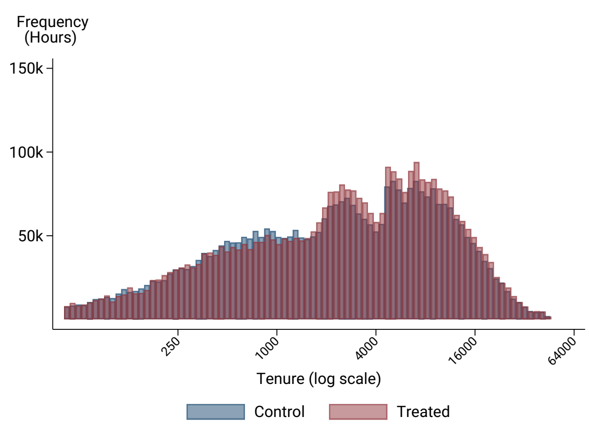
[13] This step is necessary because the empirical distribution of employment composition is not an equilibrium for two reasons. First, observed tenure is censored by the start of our sample (2016Q4), and second, real-world labor markets are unlikely to have remained unchanged for long enough to fully reach equilibrium.

Figure 8: Simulating a $1 Increase In the Minimum Wage

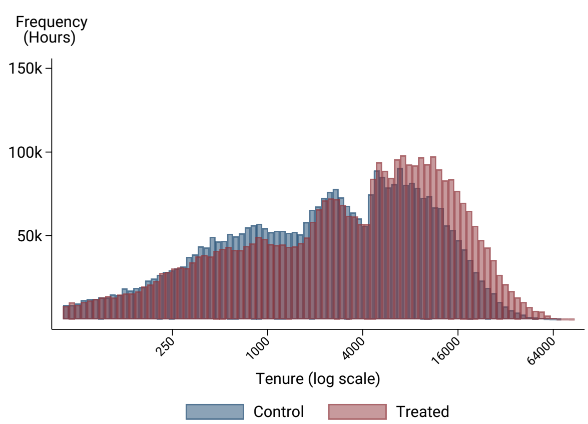
(a) Initial Equilibrium



(b) End of Fiscal Year After Minimum Wage Increase



(c) New Equilibrium After Minimum Wage Increase



the same even as the composition of staff changes. For example, we might be concerned that as a facility's staff becomes more tenured, the facility's incentive to retain high-tenure staff weakens. If so, the retention rate for tenured staff would decrease as the composition of staff becomes more tenured. Our simulation does not capture this phenomenon and could therefore overstate the long-run impacts on tenure composition. Nonetheless, these patterns indicate that small changes in hourly wages can substantially change the composition of the workforce. In the healthcare industry, such changes are also likely to affect industry performance and the quality of care.

5 Conclusion

This paper shows that higher minimum wages do not reduce employment in the nursing home sector, but do change retention and how hours are allocated across groups of workers. We find that higher minimum wages shift the allocation of hours to the most experienced workers due to both a retention and individual-worker effect. First, increases in the minimum wage reduce separations, especially among the most experienced workers. Second, those with the most experience experience the greatest increase in weekly hours, including full-time work, whereas less-experienced workers increasingly work in part-time roles. The retention effect becomes increasingly important in the first nine months after a wage increase, accounting for about two-thirds of the hours shift by the end of the period. Altogether, our findings suggest that higher wages can increase the experience-adjusted amount of services firms provide.

While many experience concerns pertain to low-wage sectors more broadly, considerations of worker experience are of particular importance in healthcare settings and the nursing home industry. Concerns about the sufficiency of nursing home staffing are long-standing (Institute of Medicine, 1986) and more recently, concerns have been raised about the industry's alarmingly high turnover rate (Gandhi et al., 2021; Abelson, 2021; Senate Finance Committee, 2021). Encouragingly, work in both nursing homes and hospital settings indicates that increases in worker retention can improve the quality of care provided (Bartel et al., 2014; Antwi and Bowblis, 2018), and separate work indicates that minimum wages improve resident health and safety in nursing homes (Ruffini, 2020). That we find higher minimum wages lead to greater retention provides a mechanism between these two relationships, and indicates that wage policies can change the nature of work in ways that affect the consumer experience.

Finally, higher minimum wages are frequently proposed as a policy to increase earnings for the lowest-wage workers. However, our findings indicate that with a full accounting of employment responses across the intensive and extensive margins, the full effect of the minimum wage on lower-tail inequality is attenuated compared to the mechanical wage compression. That highly-experienced workers receive work longer hours indicates that much of the benefits of minimum wages are received by incumbent workers.

References

Abelson, Reed, "High Staff Turnover at U.S. Nursing Homes Poses Risks for Residents' Care," https://www.nytimes.com/2021/03/01/health/covid-nursing-homes-staff-turnover.html 2021.

Antwi, Yaa Akosa and John R Bowblis, "The impact of nurse turnover on quality of care and mortality in nursing homes: evidence from the great recession," *American Journal of Health Economics*, 2018, *4* (2), 131–163.

Autor, David, Alan Manning, and Christopher L Smith, "The contribution of the minimum wage to US wage inequality over three decades: a reassessment," *American Economic Journal: Applied Economics*, 2016, *8* (1), 58–99.

Bartel, Ann P, Nancy D Beaulieu, Ciaran S Phibbs, and Patricia W Stone, "Human capital and productivity in a team environment: evidence from the healthcare sector," *American Economic Journal: Applied Economics*, 2014, *6* (2), 231–59.

Becker, Gary S, "Investment in human capital: A theoretical analysis," *Journal of political economy*, 1962, *70* (5, Part 2), 9–49.

Belman, Dale and Paul J Wolfson, *What does the minimum wage do?*, WE Upjohn Institute, 2014.

Bergman, Alon, Guy David, and Hummy Song, "'I Quit': The Role of Schedule Volatility in Employee Turnover," *Available at SSRN 3910077*, 2021.

Brochu, Pierre and David A Green, "The impact of minimum wages on labour market transitions," *The Economic Journal*, 2013, *123* (573), 1203–1235.

Bureau of Labor Statistics, "May 2019 National Industry-Specific Occupational Employment and Wage Estimates: NAICS 623100," https://www.bls.gov/oes/2019/may/naics4_623100.htm 2020.

Butschek, Sebastian, "Raising the bar: minimum wages and employers' hiring standards," *American Economic Journal: Economic Policy*, 2022.

Callaway, Brantly and Pedro HC Sant'Anna, "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 2020.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer, "The effect of minimum wages on low-wage jobs," *The Quarterly Journal of Economics*, 2019, *134* (3), 1405–1454.

Centers for Medicare and Medicaid Services, *Design for Care Compare Nursing Home Five-Star Quality Rating System: Technical User's Guide* Jan 2022.

Clemens, Jeffrey, "How do firms respond to minimum wage increases? understanding the relevance of non-employment margins," *Journal of Economic Perspectives*, 2021, *35* (1), 51–72.

— **and Michael Wither**, "The minimum wage and the Great Recession: Evidence of effects on the employment and income trajectories of low-skilled workers," *Journal of Public Economics*, 2019.

de Chaisemartin, Clément and Xavier d'Haultfoeuille, "Two-way fixed effects estimators with heterogeneous treatment effects," Technical Report, National Bureau of Economic Research 2019.

DiNardo, John, Nicole M Fortin, and Thomas Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, 1996, *64* (5), 1001–1044.

Doucouliagos, Hristos and Tom D Stanley, "Publication selection bias in minimum-wage research? A meta-regression analysis," *British Journal of Industrial Relations*, 2009, *47* (2), 406–428.

Dube, Arindrajit, "Impacts of minimum wages: review of the international evidence," *Independent Report. UK Government Publication*, 2019.

— , "Minimum wages and the distribution of family incomes," *American Economic Journal: Applied Economics*, 2019, *11* (4), 268–304.

— **, Laura Giuliano, and Jonathan Leonard**, "Fairness and frictions: The impact of unequal raises on quit behavior," *American Economic Review*, 2019, *109* (2), 620–63.

— **, T William Lester, and Michael Reich**, "Minimum wage shocks, employment flows, and labor market frictions," *Journal of Labor Economics*, 2016, *34* (3), 663–704.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams, "Sources of Geographic Variation in Health Care: Evidence From Patient Migration*," *The Quarterly Journal of Economics*, 07 2016, *131* (4), 1681–1726.

Gandhi, Ashvin, Huizi Yu, and David Grabowski, "High Nursing Staff Turnover in Nursing Homes Offers Important Quality Information," *Health Affairs*, 2021.

Gittings, R Kaj and Ian M Schmutte, "Getting handcuffs on an octopus: Minimum wages, employment, and turnover," *ILR Review*, 2016, *69* (5), 1133–1170.

Giuliano, Laura, "Minimum wage effects on employment, substitution, and the teenage labor supply: Evidence from personnel data," *Journal of Labor Economics*, 2013, *31* (1), 155–194.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

Gopalan, Radhakrishnan, Barton H. Hamilton, Ankit Kalda, and David Sovich, "State minimum wages, employment, and wage spillovers: evidence from administrative payroll data," *Journal of Labor Economics*, 2021, *39* (3), 673–707.

Hashimoto, Masanori, "Firm-specific human capital as a shared investment," *The American Economic Review*, 1981, *71* (3), 475–482.

Institute of Medicine, *Improving the quality of care in nursing homes*, National Academies Press, 1986.

Jardim, Ekaterina, Mark C Long, Robert Plotnick, Emma van Inwegen, Jacob Vigdor, and Hilary Wething, "Minimum wage increases and low-wage employment: Evidence from Seattle," Technical Report 2020.

Labor Center, "Inventory of US City and County Minimum Wage Ordinances," laborcenter.berkeley.edu/minimum-wage-living-wage-resources/inventory-of-us-city-and-county-minimum-wage-ordinances/ 2021.

Lee, David S, "Wage inequality in the United States during the 1980s: Rising dispersion or falling minimum wage?," *Quarterly Journal of Economics*, 1999, *114* (3), 977–1023.

Lemieux, Thomas, "The changing nature of wage inequality," *Journal of population Economics*, 2008, *21* (1), 21–48.

Manning, Alan, *Monopsony in motion*, Princeton University Press, 2013.

Mincer, Jacob, "Human capital, technology, and the wage structure: what do time series show?," 1991.

Mukamel, Dana B, William D Spector, Rhona Limcangco, Ying Wang, Zhanlian Feng, and Vincent Mor, "The costs of turnover in nursing homes," *Medical care*, 2009, *47* (10), 1039.

Murrin, Suzanne, "CMS Use of Data on Nursing Home Staffing: Progress and Opportunities To Do More," OIG Report OEI-04-18-00451 March 2021.

Portugal, Pedro and Ana Rute Cardoso, "Disentangling the minimum wage puzzle: an analysis of worker accessions and separations," *Journal of the European Economic Association*, 2006, *4* (5), 988–1013.

Rinz, Kevin and John Voorheis, "The Distributional Effects of Minimum Wages: Evidence from Linked Survey and Administrative Data," *United States Census Bureau, Working Paper Number: CARRA-WP-2018-02*, 2018.

Ruffini, Krista, "Worker earnings, service quality, and firm profitability: Evidence from nursing homes and minimum wage reforms," Technical Report, Unpublished working paper 2020.

Schmitt, John, "Why does the minimum wage have no discernible effect on employment," *Center for Economic and Policy Research*, 2013, *22*, 1–28.

Schneider, Daniel and Kristen Harknett, "Consequences of routine work-schedule instability for worker health and well-being," *American Sociological Review*, 2019, *84* (1), 82–114.

_ and _ , "Hard Times: Routine Schedule Unpredictability and Material Hardship among Service Sector Workers," *Social Forces*, 2021, *99* (4), 1682–1709.

Senate Finance Committee, "A National Tragedy: COVID-19 in the Nation's Nursing Homes," https://www.finance.senate.gov/hearings/a-national-tragedy-covid-19-in-the-nations-nursing-homes 2021.

Shen, Karen, "Relationship between nursing home COVID-19 outbreaks and staff neighborhood characteristics," *medRxiv*, 2020.

_ , Brian McGarry, David C. Grabowski, Jonathan Gruber, and Ashvin Gandhi, "Nursing Home Staffing Patterns during COVID-19 Outbreaks," *Unpublished Manuscript*, 2022.

A Appendix

A.1 Defining Nursing Home Labor Market Concentration

This section describes how we construct a facility-specific measure of nursing home labor market concentration which is used to focus on facilities in low-concentrated labor markets. In brief, the measure is constructed in two steps: first, we measure the level of labor market concentration a potential worker faces given the choice set of employment options at nearby nursing homes. Second, we take the facility-level average across all potential workers in order to capture the level of concentration that each facility faces in the local labor market. This calculation is conducted at the census block level by using the number of potential employees in residence as weights.

A.1.1 Longitudinal Employer-Household Dynamics Data

In order to construct the local labor market concentration, we first define the geographical boundary of a local labor market. Despite the difficulty in determining the exact boundary of a local labor market, we can approximate this using the physical distance that a worker is likely to be willing to commute to a potential employer. Thus, in our simplified model, supply of the labor market around each facility is the sum of all the potential workers that reside within this travel distance from the facility. To achieve this, we take advantage of the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) data, which contains commute flow dynamics between census blocks. The data is comprised of three distinct file types as shown in Table A1.

Appendix Table A1: LODES Data File Descriptions

File Type	Description	Uses
Origin-Destination	Contains workplace block, residence block, and the number of jobs (in all service sectors outside of the trade, transportation, and utilities) between the workplace and residence blocks	Used to compute the commute distance of a potential nursing home employee, and to measure the commute flow size.
Workplace Area Characteristics	Contains workplace block and the number of jobs in the Health Care and Social Assistance sector	Used to algorithmically match workplace blocks to the nurse staffing data.
Residence Area Characteristics	Contains residence block and the number of jobs in the Health Care and Social Assistance sector	Used to weight block-level HHI.

A useful feature of the Origin-Destination (OD) data is that it provides the employment distribution of each workplace block over the residential census blocks, categorized by multiple workforce characteristics. This allows us to estimate the distributions of commuting distance and commute time of all potential workers. Further details are described in Section A.1.2. In order to determine the potential nursing home labor market, we use the number service sector jobs outside of the trade, transportation, and utilities industries, (the narrowest service sector categorization available in the LODES data). Secondly, we combine the OD data with the Residence Area Characteristics (RAC) data in order to approximate the number of potential nursing home workers living in the corresponding residence blocks.

We match the corresponding workplace blocks to the nursing home coordinates. In order to overcome possible mismatches due to the lack of precision in the data, we check for the quality of a potential match using the Workplace Area Characteristics (WAC) data by comparing the block level workforce distribution in the WAC data to the number of workers at the facility. We thus pick the number of healthcare and social assistance jobs from the WAC data and implement the following algorithm:

1. Classify census blocks around each facility into three levels of match priority based on the distance from the facility, with cutoffs at 0.25km, 0.5km, and 1km.

2. For each facility-block pair, compute the ratio between the number of jobs in the workplace block and the the number of jobs at the facility.[14] If the ratio is too low, it implies that the matched block may not be adequately capturing the workplace employment distribution as evident in the nurse staffing data, and thus signals a mismatch.

3. Starting with the first distance-bin, identify all the block-facility matches whose ratio is greater than 0.5. If such a pair exists, assign the facility to the block whose ratio is closest to 1.

4. If multiple facilities were assigned to the same block, recompute the ratio, but between the number of jobs in the workplace block and the number of jobs of all facilities in the matched block.

5. If the block level ratio < 0.5, iteratively reassign these facilities to the remaining census blocks, prioritizing the closest facility-block pair that has the facility level ratio closest to 1.

6. For all other facilities without any match, assign it to the closest block with the ratio closest to 1 regardless of the condition on the ratio.

After running the algorithm, facilities are assigned their best matched census blocks, which are subsequently merged with the Origin-Destination commute flow data and the Residence Area Characteristics data to construct the HHI, as detailed in the next section. Figure A1a and Figure A1b respectively show the locations of the residence of workers from the Origin-Destination data whom we have matched to the facilities, marked by the $\times$ symbol. We can see that the focal facility has competing facilities nearby on this map, which would hypothetically be competing for the same workers in their local labor market.

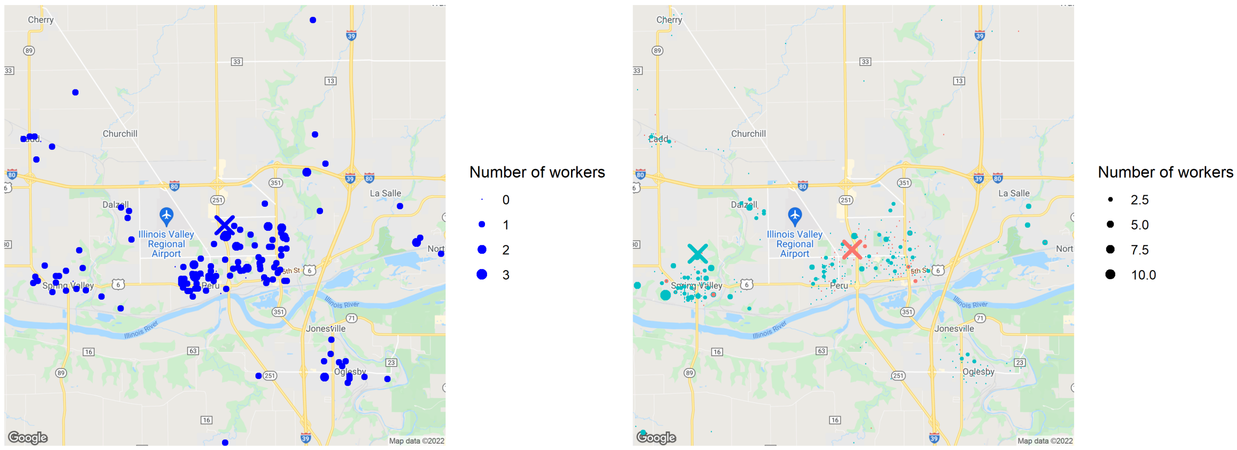
A.1.2 Computing HHI

Using the Origin-Destination data for the matched facility-block pairs above, the next step identifies all the facilities that constitute a potential worker's choice set conditional on the worker's area of residence.

[14] We compute each facility's employment size using the first full quarter available in the Payroll Based Journal data in order to account for the facilities with different entry dates.

Appendix Figure A1: Residence blocks of workers matched to each facility

(a) Focal **(b) Competition**



In order to obtain a realistic representation of how far a worker may be willing to commute, rather than simply measuring the geodesic distance, we implement the Bing Maps Distance Matrix API to measure the driving distance and travel time.[15] Then, for each commuting zone (demarcated by the Bureau of Economic Analysis shapefiles) in which facilities are located, we measure the threshold for commute time as the 75th percentile of commute flows.[16]

We then identify the employer choice set facing the worker. For each potential worker's residence block, employment options of working at a nursing home are taken to be the facilities within the 75 percentile commute time threshold, again obtained using the actual driving time between the residence block and all nearby facilities.[17] Then for each block, we measure the level of market concentration a potential worker faces as the Herfindahl index for block b:

$$Block\ HHI_b = \sum_{f \in F_b} \left(\frac{W_f}{\sum\limits_{f \in F_b} W_f} \right)^2, \; F_b = \{\text{Facilities within } t_{75} \text{ driving time from Block } b\},$$

where W_f is the number of nurses employed by facility f in the first full quarter, and t_{75} is the 75th percentile commute zone specific commute time.

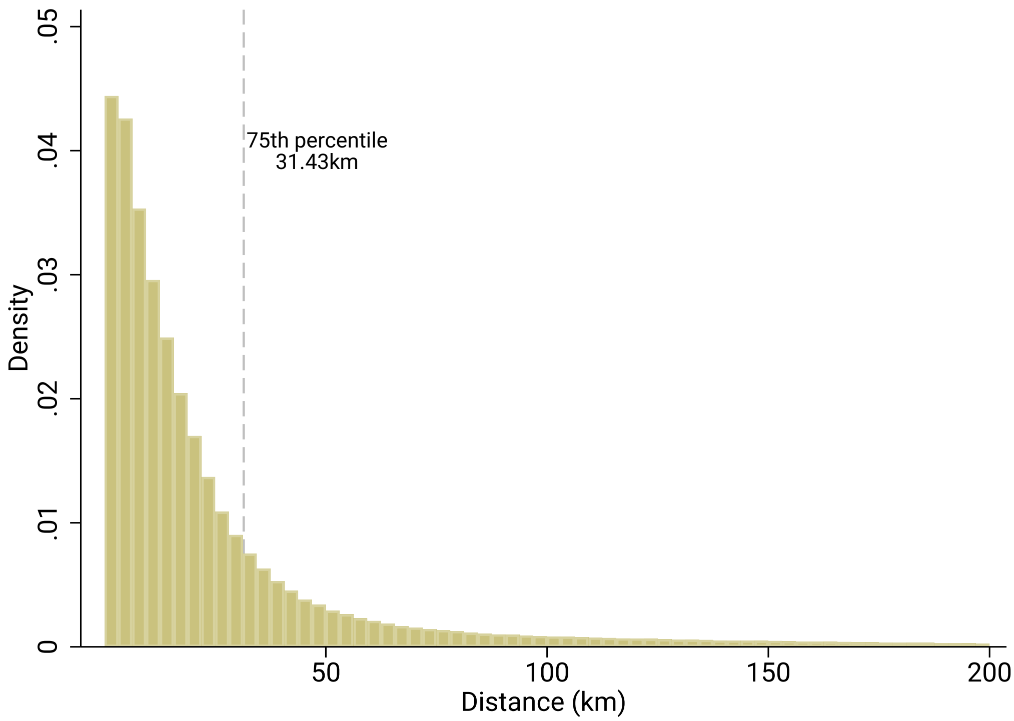
We next aggregate the block-level labor market concentration to the facility level by taking the average of the block level HHI, weighted by the number of potential workers living in the block (proxied by the

[15] To ensure consistency, the traffic data collected are from July 14 2019 at 8AM.

[16] Outliers are winsorized at one hour.

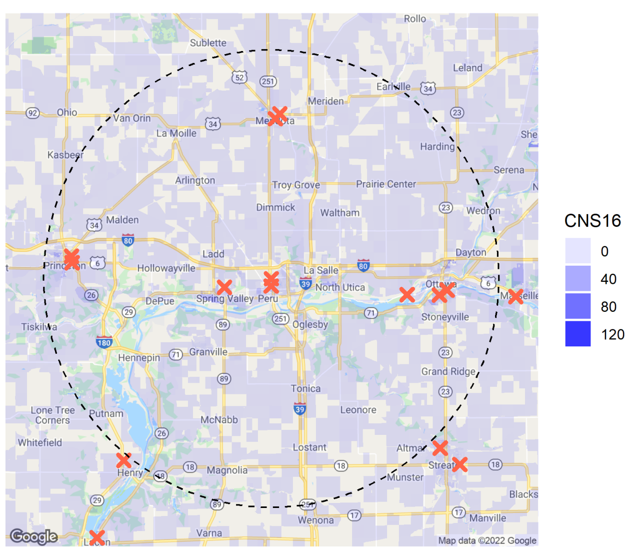
[17] For computational efficiency, we restrict our traffic data queries to those that are physically close. We use the geodesic distance of 31.43km, a 75th percentile of all commute flows, as the threshold for making the queries. In about 1 percent of cases, the facility-block pair is more than 31.43km apart, but still lies within the commute time threshold (e.g. there may be relatively little traffic). In such cases, we estimate the commute time as the geodesic distance scaled by the commute zone specific average speed.

Appendix Figure A2: Distribution of Commute Distance to Nursing Homes



Note: 3.37% of the commute distances above 200 km are not shown in the figure.

Appendix Figure A3: Competing facilities within the focal facility's labor market



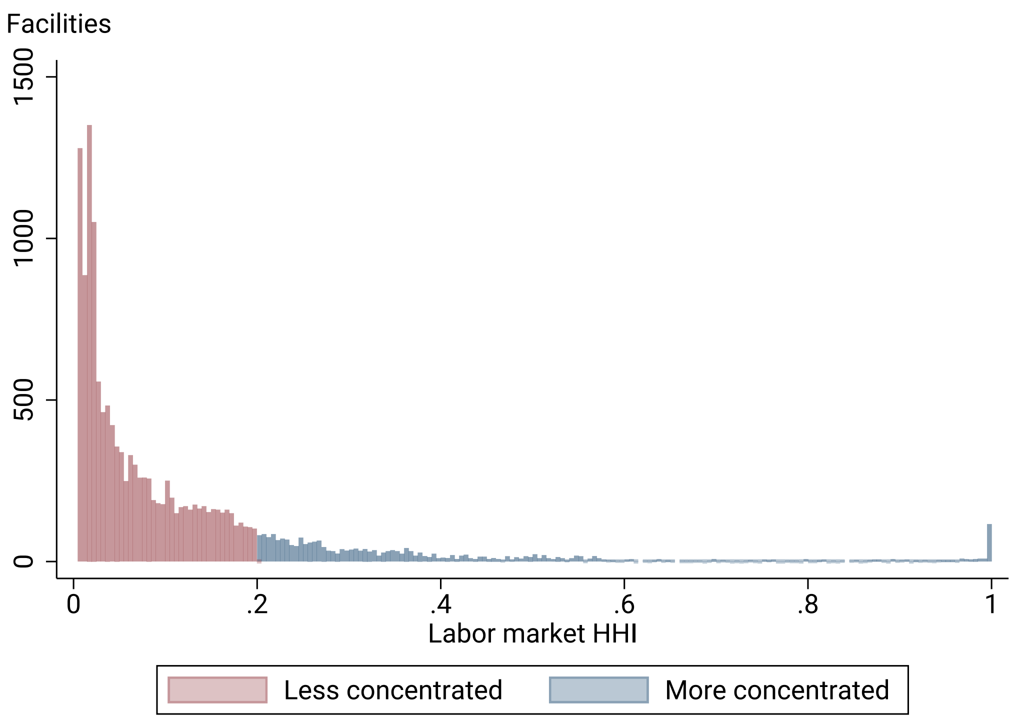
Note: The dotted circle represents the boundary of the focal facility's local labor market. Census blocks are colored according to the total number of potential employees in residence, classified under Health Care and Social Assistance (CNS16) in the Residence Area Characteristics data. Facilities are marked by the red × symbol.

number of Health Care and Social Assistance jobs from the RAC file). This is represented by Figure A3, which shows the distribution of potential workers the focal facility is likely to be competing for with nearby competiting facilities.

$$Facility\ HHI_f = \frac{\sum\limits_{b \in B_f} R_b \times Block\ HHI_b}{\sum\limits_{b \in B_f} R_b},\ B_f = \{\text{Blocks within } t_{75} \text{ driving time from Facility } f\},$$

where R_b is the number of nurses living in block b. Figure A4 plots the HHI of the facilities divided at 0.2 (approximately the 80th percentile). The distribution is highly skewed to the right, with most facilities generally facing very high levels of competition in the local labor market. Our analytical sample focuses on facilities in the less concentrated markets.

Appendix Figure A4: Distribution of Labor Market HHI



A.2 Minimum Wage Statistics

Appendix Table A2: Minimum Wage Summary Statistics

	Fiscal Year		
	2017	2018	2019
Minimum Minimum Wage	7.25	7.25	7.25
Maximum Minimum Wage	13.00	15.00	15.65
Mean Minimum Wage	8.85	9.49	10.26
Median Minimum Wage	8.25	9.25	10.10
Share of Facilities Experienced A Minimum Wage Change	0.58	0.65	0.77
Average Size of Minimum Wage Changes	0.58	0.55	0.70

A.3 Calculating lower-tail wage inequality

CNAs with up to four years of experience earn about 3.5 percent more than CNAs with less than a year of experience (Payscale.com). In order to provide an estimate of the mechanical and full effect of minimum wages on earnings inequality within the CNA workforce, we proceed in three steps. We first take average wage information for workers with less than a year of experience and those with 1-4 years of experience, multiplied by average hours, and calculate the baseline earnings ratio. New hires are considered those with less than a year of experience, those with 1-4 years of experience are in the third experience tercile. Second, we apply the earnings elasticities and estimate post-minimum wage earnings for a 10 percent increase in the minimum wage using the elasticities in (Ruffini, 2020). We assume that new hires receive higher wages due to the minimum wage, but spillovers do not extend to the most experienced workers. We then calculate the mechanical change in earnings inequality from the wage changes alone. Third, we incorporate hours responses by applying the tercile-specific estimates of changes in hours from Figure 6 to baseline hours and multiply by the wage rate.

A.4 Less-binding areas: Pay-ratio in top 40 percent

Appendix Table A3: Hours and Number of Employees per Bed, by Occupation and Pay Type

	CNA Positions			Other Nursing Staff		Occupancy Rate
	Wage	Contract	Salaried	LPN	RN	
Panel A: Weekly Hours per Bed						
Minimum Wage	0.093	-0.015	0.008	0.037	-0.027	0.001
	(0.049)	(0.013)	(0.008)	(0.020)	(0.015)	(0.001)
Mean	12.92	0.36	0.06	4.80	2.88	0.83
Std. Dev.	4.29	1.16	0.77	2.29	2.62	0.16
Implied Representative Elasticity	0.064	-0.375	1.162	0.068	-0.082	0.006
Panel B: Weekly Payroll per Bed						
Minimum Wage	0.002	-0.000	0.000	0.001	-0.000	
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	
Mean	0.50	0.04	0.00	0.18	0.13	
Std. Dev.	0.23	0.12	0.03	0.10	0.21	
Implied Representative Elasticity	0.030	-0.084	0.379	0.047	-0.017	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility × FY	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	1,532	1,532	1,532	1,532	1,532	1,532
Facilities	9,556	9,556	9,556	9,556	9,556	9,556
Facility-Weeks	916,766	916,766	916,766	916,766	916,766	916,766

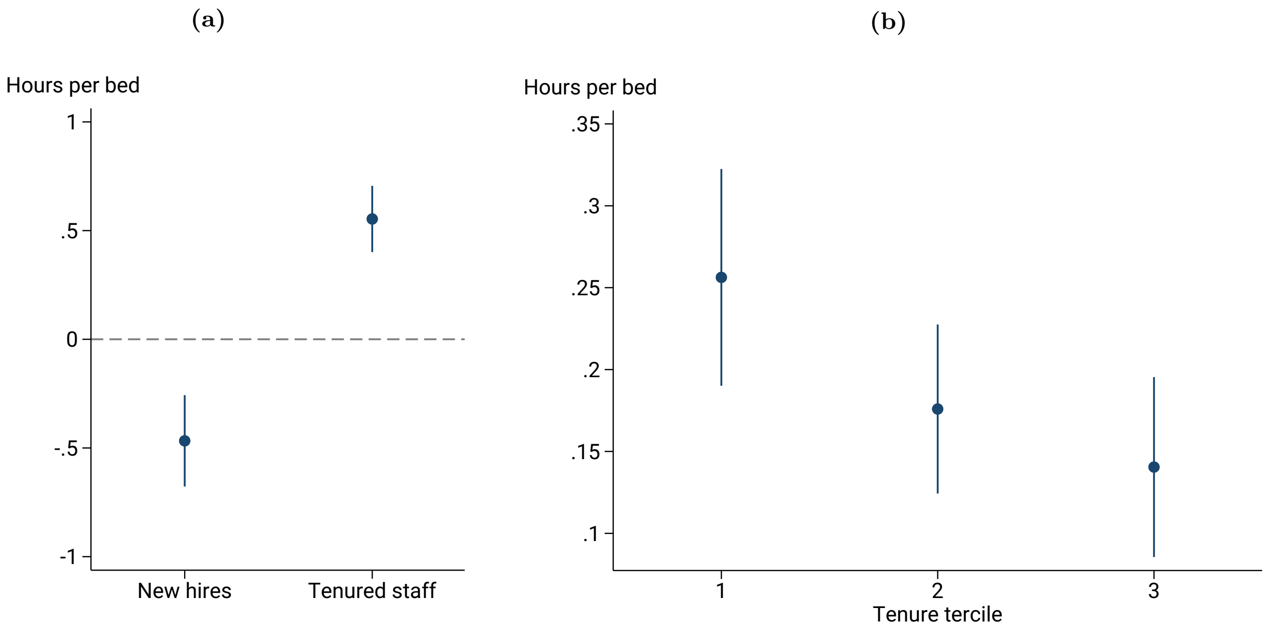
Appendix Table A4: Worker Flows - Hires/Separations Rates

	New Hires (% of payroll)	Separations (% of payroll)				
		All	New Hires	Tercile 1	Tercile 2	Tercile 3
Minimum Wage	0.029	-0.088	0.298	0.084	-0.036	-0.076
	(0.046)	(0.019)	(0.082)	(0.046)	(0.022)	(0.014)
Mean	1.65	1.63	4.33	1.64	1.00	0.53
Std. Dev.	13.54	3.27	11.13	5.86	4.36	3.67
Implied Representative Elasticity	0.155	-0.477	0.607	0.452	-0.321	-1.263
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility × FY	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	1,532	1,532	1,532	1,532	1,532	1,518
Facilities	9,556	9,556	9,556	9,556	9,556	9,556
Facility-Weeks	916,766	916,766	916,766	916,766	916,766	916,766

Appendix Table A5: Shift Length of of Hires and Separations

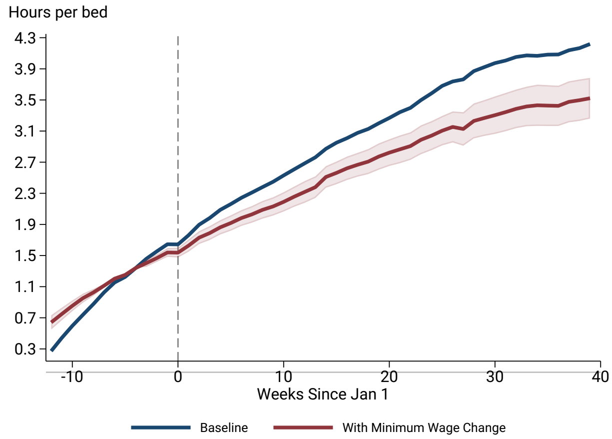
	Retained Hires	Hires				Separations			
		No Hours [0, 0]	Very Part-Time (0, 20)	Part-Time [20, 35)	Full-Time [35, ∞)	No Hours [0, 0]	Very Part-Time (0, 20)	Part-Time [20, 35)	Full-Time [35, ∞)
Panel A: 26 Weeks									
Minimum Wage	-0.000	0.003	-0.000	-0.001	-0.002	-0.002	-0.005	0.004	0.003
	(0.003)	(0.005)	(0.002)	(0.004)	(0.005)	(0.004)	(0.002)	(0.003)	(0.003)
Mean	0.17	0.54	0.08	0.15	0.23	0.56	0.09	0.16	0.19
Std. Dev.	0.33	0.44	0.24	0.31	0.37	0.45	0.25	0.33	0.35
Implied Representative Elasticity	-0.019	0.050	-0.042	-0.059	-0.064	-0.029	-0.529	0.235	0.131
Panel B: 13 Weeks									
Minimum Wage	0.000	0.005	-0.005	-0.001	0.001	-0.000	-0.006	0.002	0.004
	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)	(0.003)
Mean	0.31	0.41	0.11	0.20	0.28	0.46	0.12	0.20	0.22
Std. Dev.	0.41	0.43	0.27	0.35	0.39	0.45	0.29	0.36	0.37
Implied Representative Elasticity	0.013	0.103	-0.418	-0.043	0.036	-0.001	-0.412	0.083	0.155
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility × FY	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	1,532	1,532	1,532	1,532	1,532	1,532	1,532	1,532	1,532
Facilities	9,556	9,556	9,556	9,556	9,556	9,556	9,556	9,556	9,556
Facility-Weeks	916,766	916,766	916,766	916,766	916,766	916,766	916,766	916,766	916,766

Appendix Figure A5: Hours per Bed, CNAs by Tenure

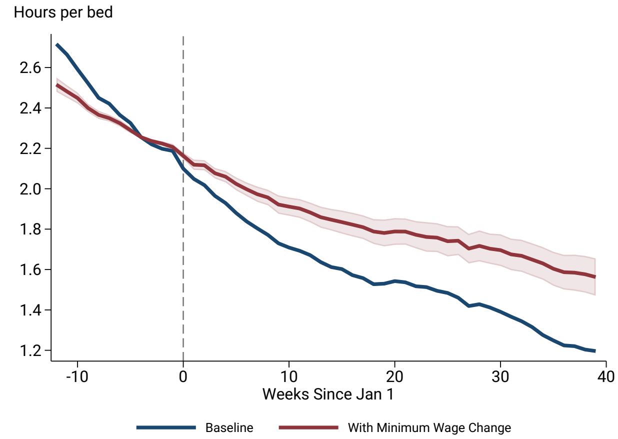


Appendix Figure A6: Dynamic Effects of Minimum Wages on Hours Worked

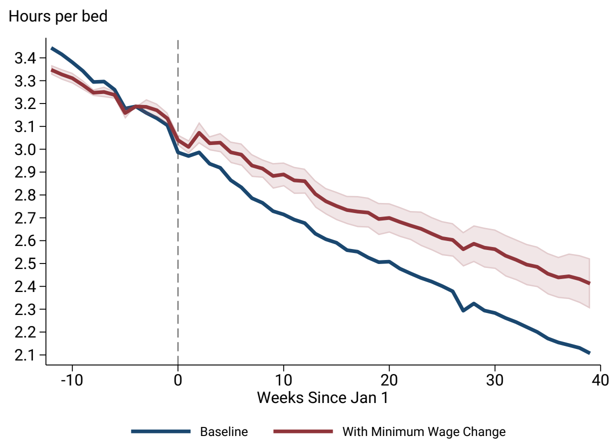
(a) New Hires



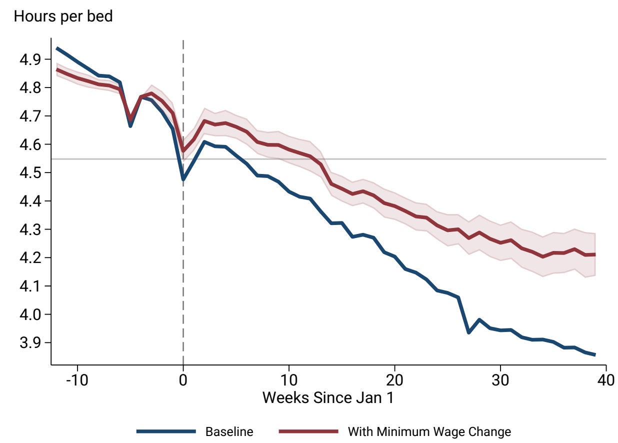
(b) 1st Tenure Tercile



(c) 2nd Tenure Tercile

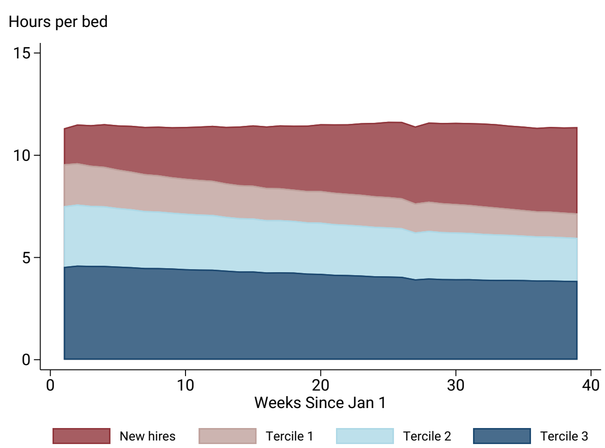


(d) 3rd Tenure Tercile

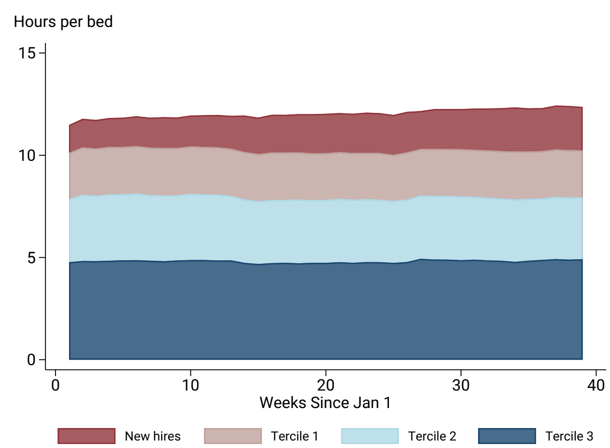


Appendix Figure A7: Overall Change in Hours Worked, by Tenure

(a) No Minimum Wage

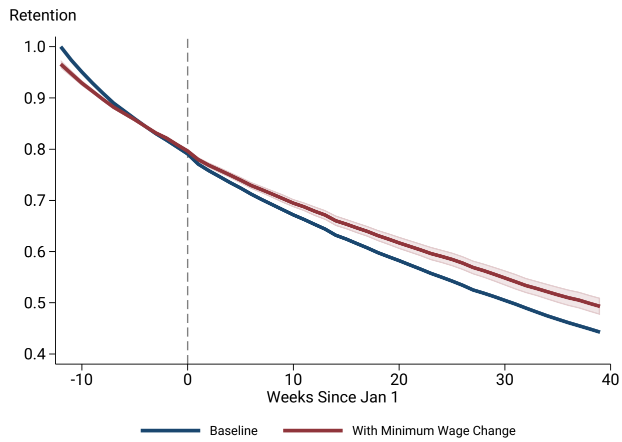


(b) Minimum Wage, Jan 2018 or Jan 2019

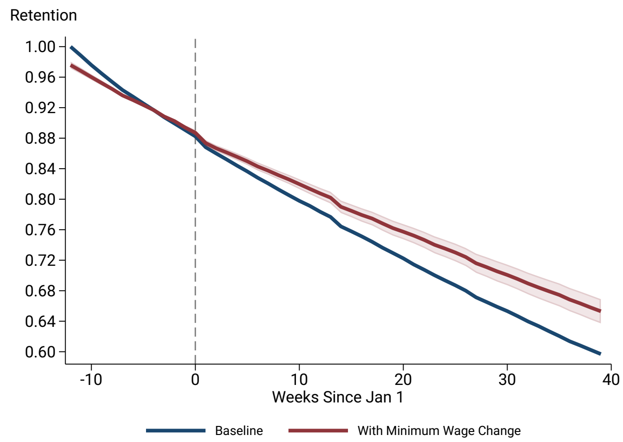


Appendix Figure A8: Retention

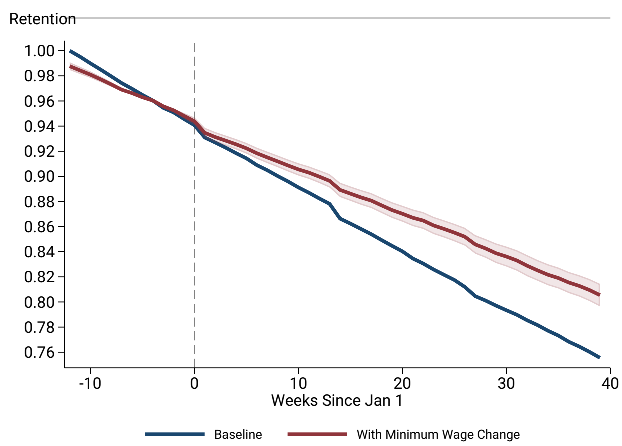
(a) 1st Tenure Tercile



(b) 2nd Tenure Tercile

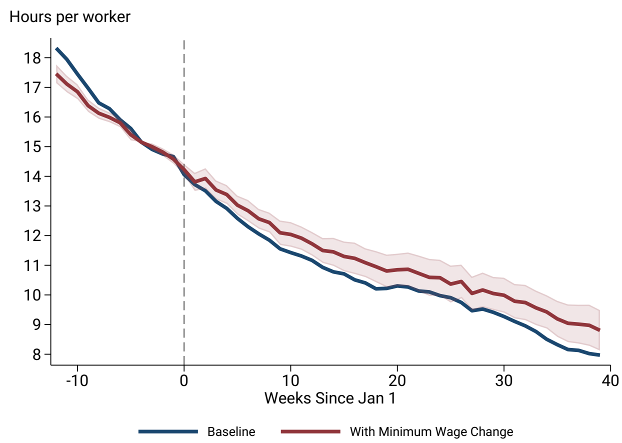


(c) 3rd Tenure Tercile

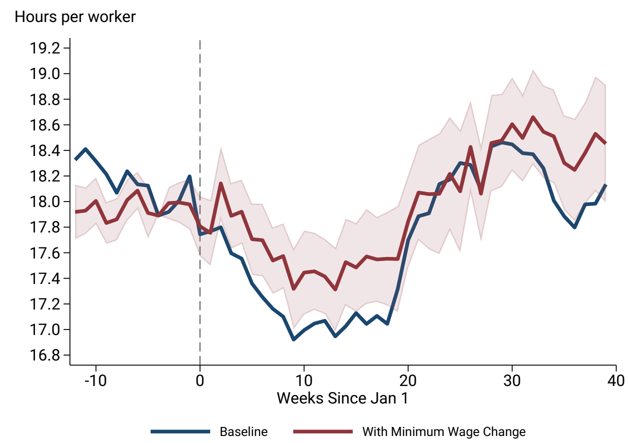


Appendix Figure A9: Changes in Hours per Worker, With and Without Changes in Retention

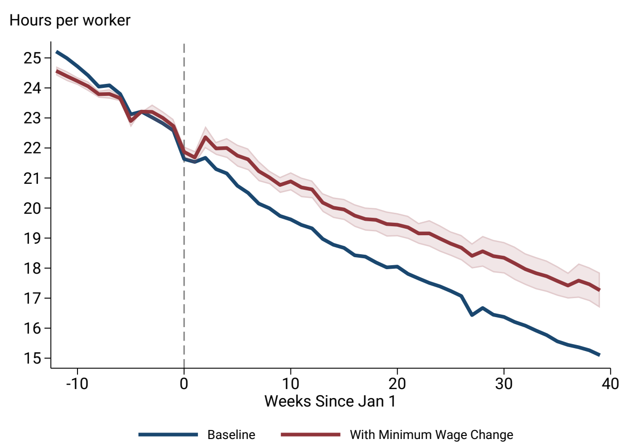
(a) Tercile 1, with Retention Effect



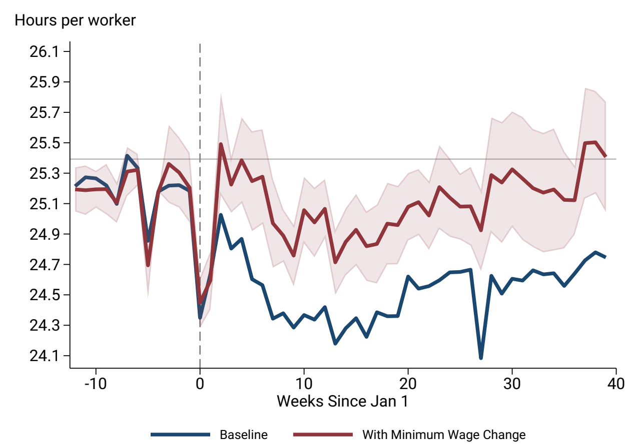
(b) Tercile 1, per Retained Worker



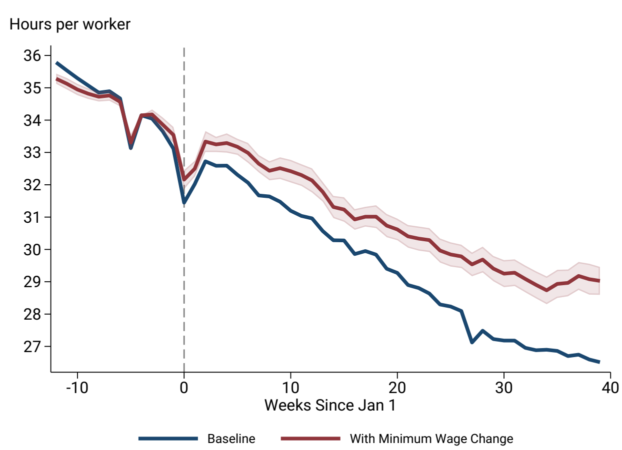
(c) Tercile 2, with Retention Effect



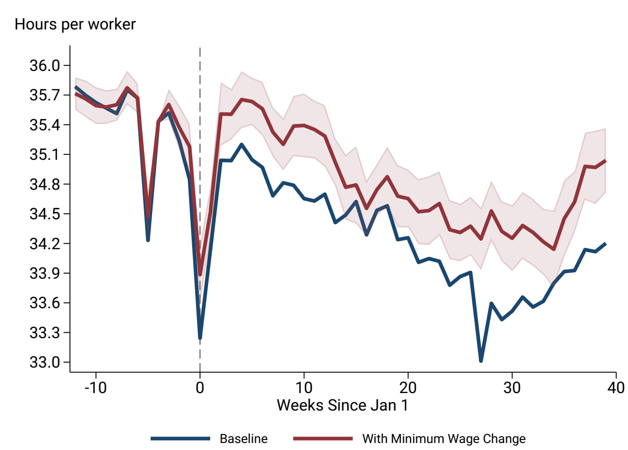
(d) Tercile 2, per Retained Worker



(e) Tercile 3, with Retention Effect

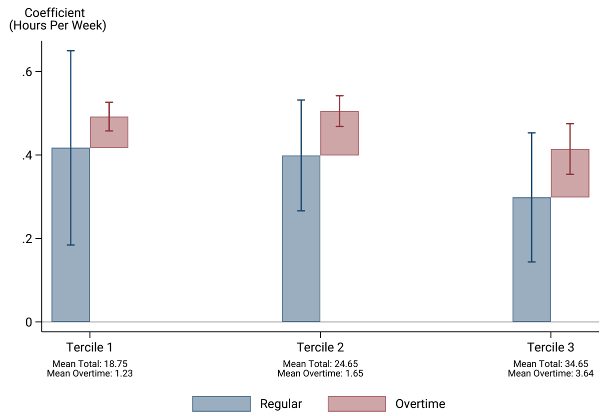


(f) Tercile 3, per Retained Worker

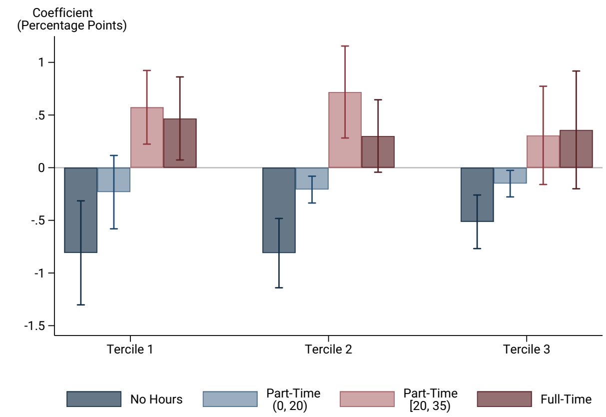


Appendix Figure A10: Characteristics of Low-Wage Work

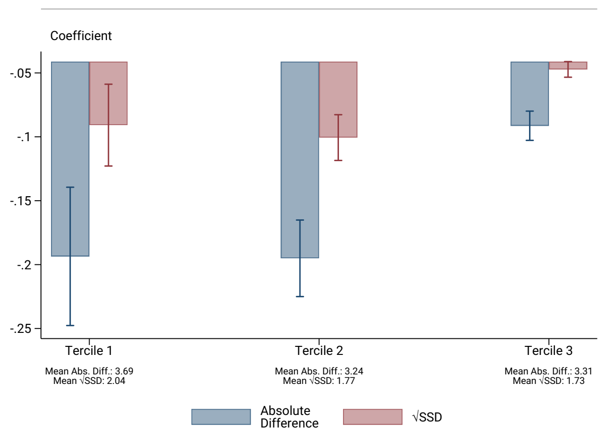
(a) Hours Per Worker



(b) Part-Time and Full-Time



(c) Scheduling Volatility



A.5 Robustness, Separate Facility and Fiscal Year Fixed Effects

Appendix Table A6: Hours and Number of Employees per Bed, by Occupation and Pay Type

	CNA Positions			Other Nursing Staff		Occupancy Rate
	Wage	Contract	Salaried	LPN	RN	
Panel A: Weekly Hours per Bed						
Minimum Wage	0.183	-0.044	0.014	0.063	0.008	0.001
	(0.126)	(0.020)	(0.008)	(0.033)	(0.029)	(0.001)
Mean	13.06	0.35	0.07	4.68	2.84	0.82
Std. Dev.	4.21	1.10	0.88	2.39	2.54	0.15
Implied Representative Elasticity	0.139	-1.258	1.944	0.133	0.028	0.011
Panel B: Weekly Payroll per Bed						
Minimum Wage	0.001	-0.003	0.000	-0.000	-0.001	
	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	
Mean	0.51	0.04	0.00	0.17	0.12	
Std. Dev.	0.21	0.12	0.04	0.10	0.20	
Implied Representative Elasticity	0.016	-0.731	0.194	-0.013	-0.050	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility × FY	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	673	673	673	673	673	673
Facilities	3,907	3,907	3,907	3,907	3,907	3,907
Facility-Weeks	342,657	342,657	342,657	342,657	342,657	342,657

Appendix Table A7: Worker Flows - Hires/Separations Rates

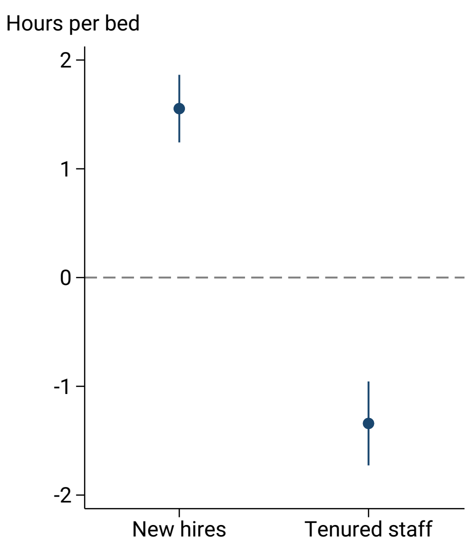
	New Hires (% of payroll)	Separations (% of payroll)				
		All	New Hires	Tercile 1	Tercile 2	Tercile 3
Minimum Wage	0.034	0.076	-1.371	-0.367	-0.071	-0.023
	(0.023)	(0.024)	(0.218)	(0.055)	(0.033)	(0.019)
Mean	1.62	1.62	4.25	1.62	1.00	0.54
Std. Dev.	7.57	3.34	11.07	5.88	4.37	3.82
Implied Representative Elasticity	0.205	0.461	-3.187	-2.231	-0.704	-0.430
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility × FY	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	673	673	673	673	673	666
Facilities	3,907	3,907	3,907	3,907	3,907	3,907
Facility-Weeks	342,657	342,657	342,657	342,657	342,657	342,657

Appendix Table A8: Shift Length of of Hires and Separations

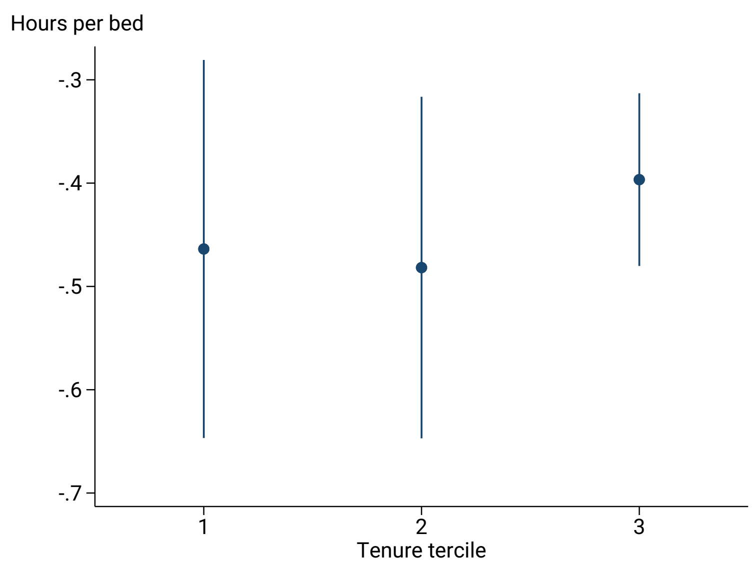
	Retained Hires	Hires				Separations			
		No Hours [0, 0]	Very Part-Time (0, 20)	Part-Time [20, 35)	Full-Time [35, ∞)	No Hours [0, 0]	Very Part-Time (0, 20)	Part-Time [20, 35)	Full-Time [35, ∞)
Panel A: 26 Weeks									
Minimum Wage	-0.078	0.016	0.003	-0.006	-0.013	-0.008	-0.002	0.003	0.007
	(0.009)	(0.004)	(0.003)	(0.003)	(0.004)	(0.007)	(0.003)	(0.003)	(0.003)
Mean	0.17	0.53	0.08	0.17	0.22	0.56	0.09	0.17	0.18
Std. Dev.	0.33	0.44	0.24	0.32	0.37	0.45	0.26	0.33	0.35
Implied Representative Elasticity	-4.418	0.295	0.341	-0.341	-0.564	-0.134	-0.259	0.157	0.394
Panel B: 13 Weeks									
Minimum Wage	-0.105	0.005	0.001	-0.006	0.000	-0.007	-0.005	0.004	0.008
	(0.008)	(0.004)	(0.002)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.003)
Mean	0.32	0.40	0.11	0.22	0.27	0.45	0.13	0.21	0.21
Std. Dev.	0.41	0.43	0.27	0.36	0.39	0.45	0.30	0.37	0.36
Implied Representative Elasticity	-3.222	0.120	0.099	-0.270	0.001	-0.154	-0.383	0.188	0.377
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility × FY	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	673	673	673	673	673	673	673	673	673
Facilities	3,907	3,907	3,907	3,907	3,907	3,907	3,907	3,907	3,907
Facility-Weeks	342,657	342,657	342,657	342,657	342,657	342,657	342,657	342,657	342,657

Appendix Figure A11: Hours per Bed, CNAs by Tenure

(a)



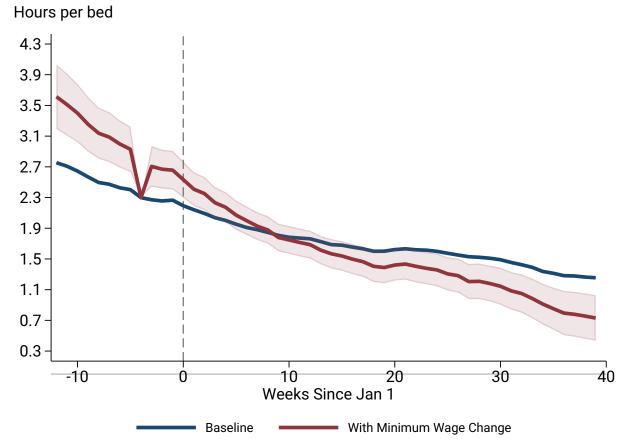
(b)



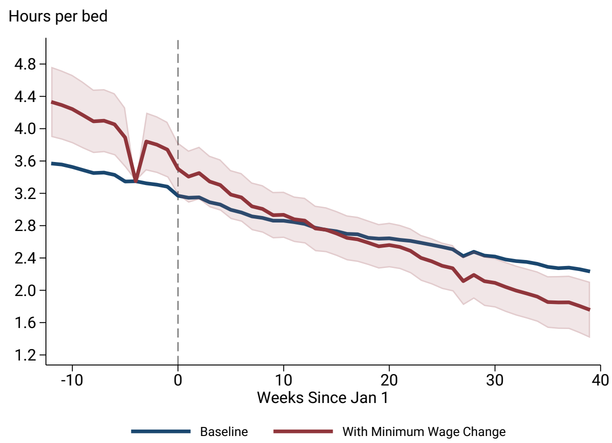
Appendix Figure A12: Dynamic Effects of Minimum Wages on Hours Worked

(a) New Hires

(b) 1st Tenure Tercile



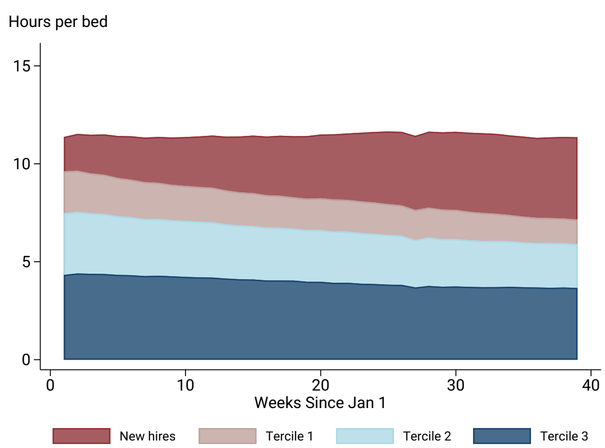
(c) 2nd Tenure Tercile



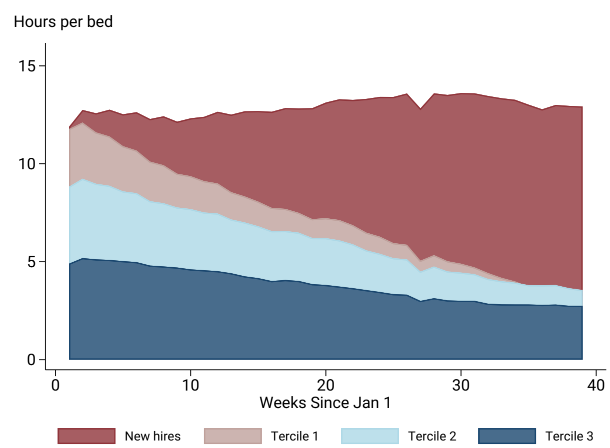
(d) 3rd Tenure Tercile

Appendix Figure A13: Overall Change in Hours Worked, by Tenure

(a) No Minimum Wage

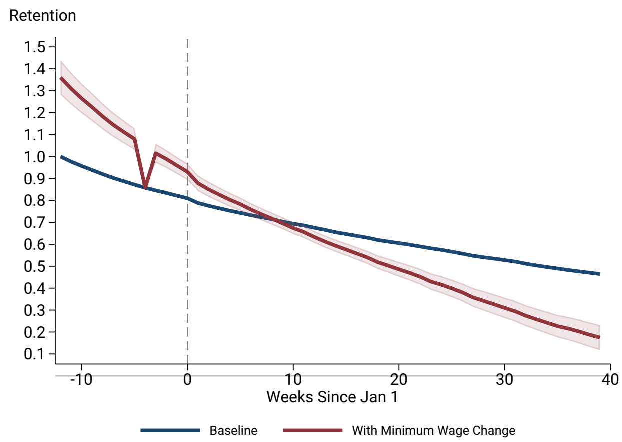


(b) Minimum Wage, Jan 2018 or Jan 2019

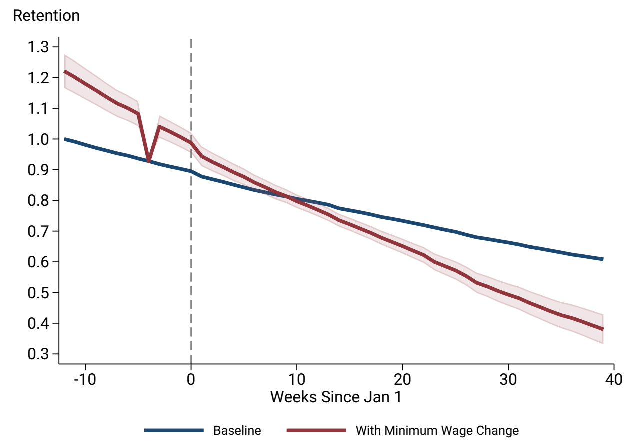


Appendix Figure A14: Retention

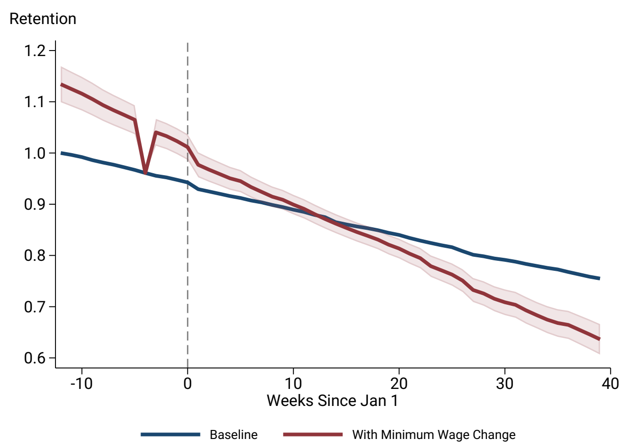
(a) 1st Tenure Tercile



(b) 2nd Tenure Tercile

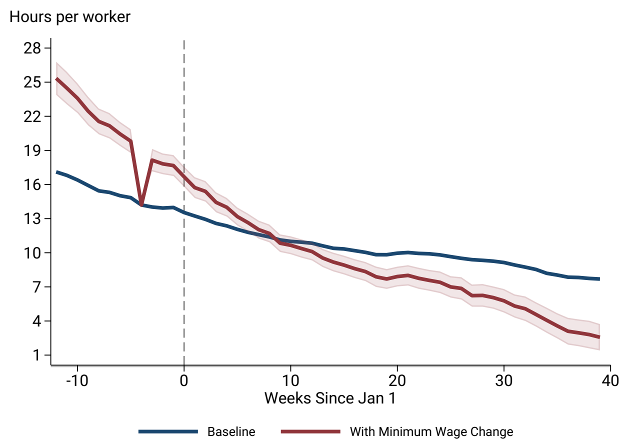


(c) 3rd Tenure Tercile

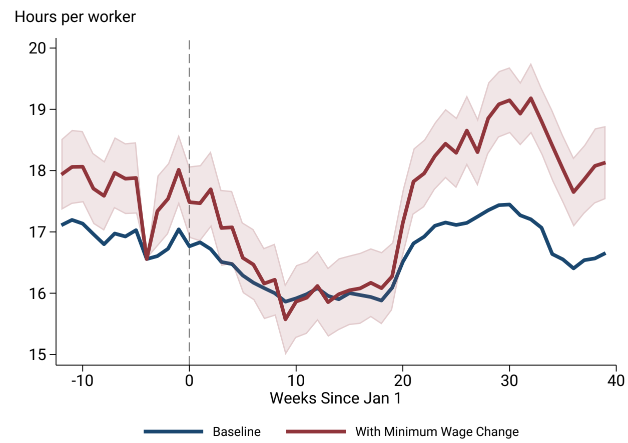


Appendix Figure A15: Changes in Hours per Worker, With and Without Changes in Retention

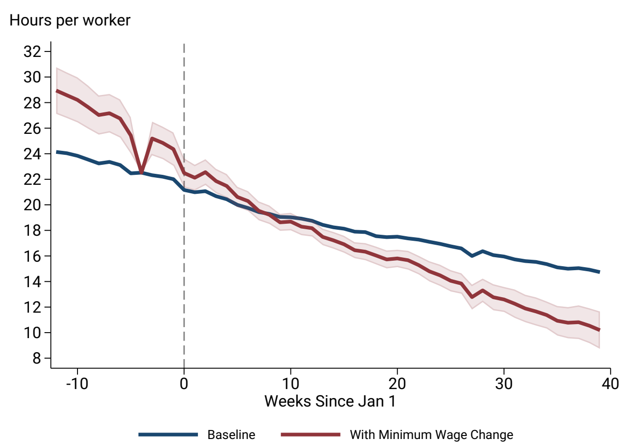
(a) Tercile 1, with Retention Effect



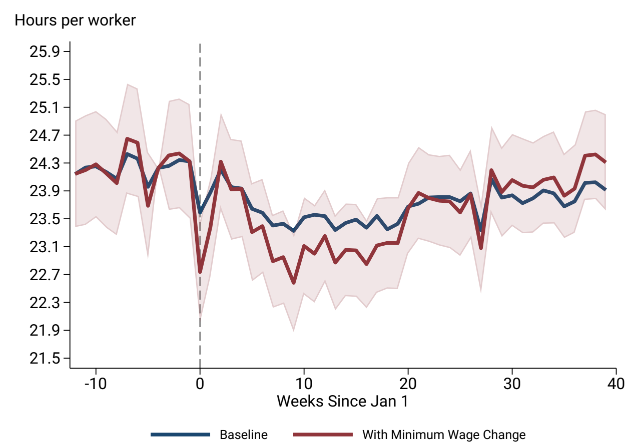
(b) Tercile 1, per Retained Worker



(c) Tercile 2, with Retention Effect



(d) Tercile 2, per Retained Worker

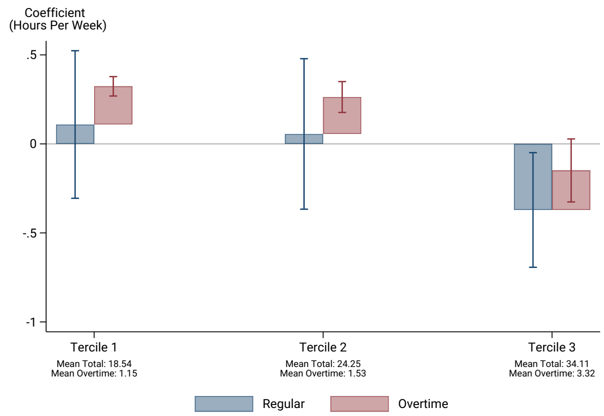


(e) Tercile 3, with Retention Effect

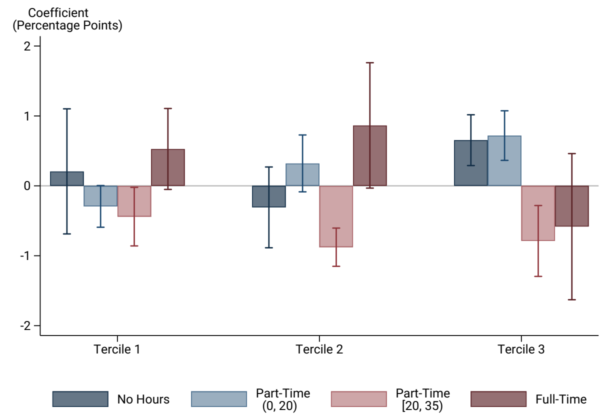
(f) Tercile 3, per Retained Worker

Appendix Figure A16: Characteristics of Low-Wage Work

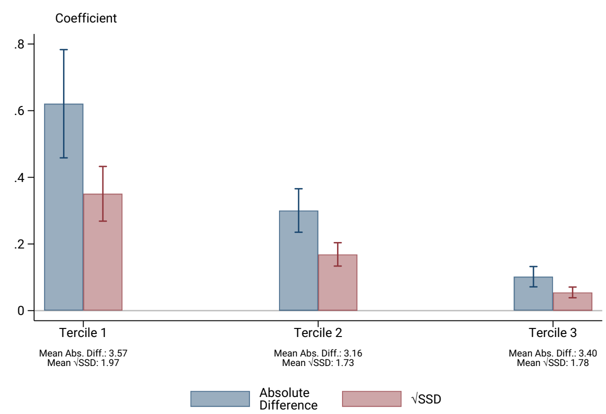
(a) Hours Per Worker



(b) Part-Time and Full-Time



(c) Scheduling Volatility



A.6 Robustness, Matched Sample

Appendix Table A9: Hours and Number of Employees per Bed, by Occupation and Pay Type

	CNA Positions			Other Nursing Staff		Occupancy Rate
	Wage	Contract	Salaried	LPN	RN	
Panel A: Weekly Hours per Bed						
Minimum Wage	0.290	0.002	0.008	0.104	-0.028	0.003
	(0.117)	(0.051)	(0.020)	(0.050)	(0.026)	(0.003)
Mean	12.24	0.39	0.05	4.38	2.59	0.79
Std. Dev.	3.82	1.11	0.62	1.87	1.85	0.16
Implied Representative Elasticity	0.225	0.047	1.433	0.225	-0.103	0.035
Panel B: Weekly Payroll per Bed						
Minimum Wage	0.010	-0.001	-0.000	0.003	0.003	
	(0.003)	(0.002)	(0.000)	(0.001)	(0.001)	
Mean	0.49	0.05	0.00	0.16	0.11	
Std. Dev.	0.18	0.12	0.02	0.07	0.12	
Implied Representative Elasticity	0.192	-0.185	-0.276	0.203	0.245	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility × FY	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	599	599	599	599	599	599
Facilities	3,573	3,573	3,573	3,573	3,573	3,573
Facility-Weeks	311,072	311,072	311,072	311,072	311,072	311,072

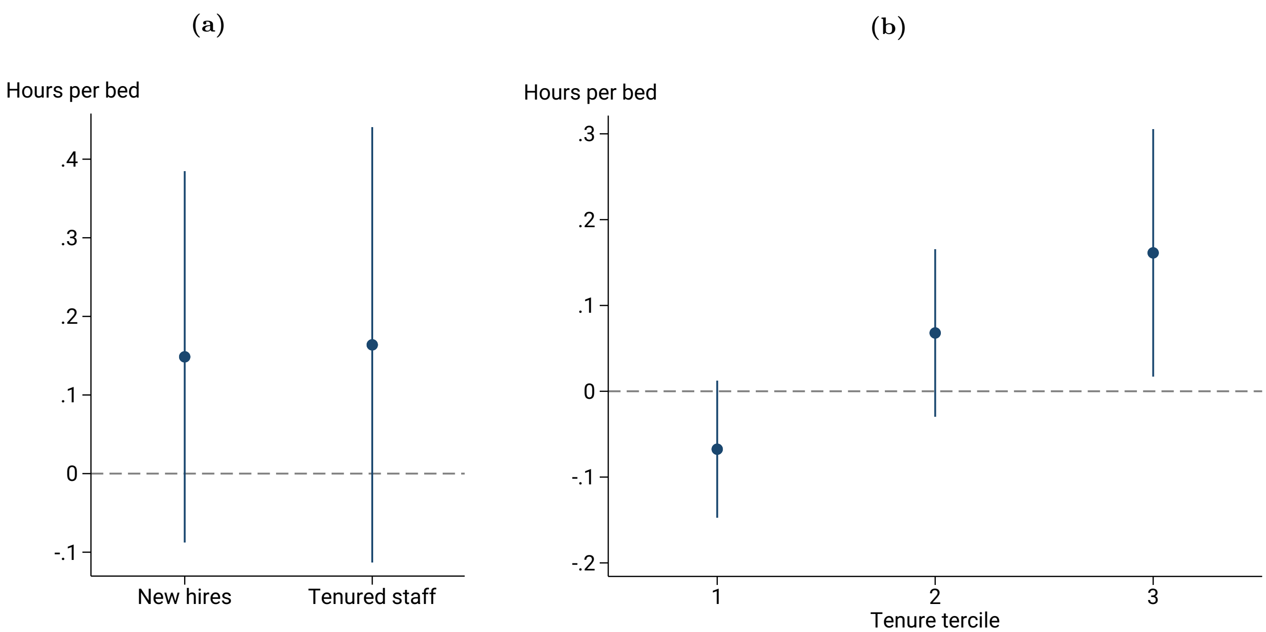
Appendix Table A10: Worker Flows - Hires/Separations Rates

	New Hires (% of payroll)	Separations (% of payroll)				
		All	New Hires	Tercile 1	Tercile 2	Tercile 3
Minimum Wage	0.178	-0.020	0.403	-0.474	-0.071	-0.010
	(0.066)	(0.060)	(0.344)	(0.159)	(0.048)	(0.050)
Mean	1.55	1.62	4.32	1.63	1.01	0.58
Std. Dev.	3.67	3.54	11.38	5.73	4.45	3.92
Implied Representative Elasticity	1.087	-0.116	0.885	-2.752	-0.668	-0.170
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week $\times$ Cohort	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility $\times$ FY	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	599	599	597	599	599	588
Facilities	3,573	3,573	3,573	3,573	3,573	3,573
Facility-Weeks	311,072	311,072	311,072	311,072	311,072	311,072

Appendix Table A11: Shift Length of of Hires and Separations

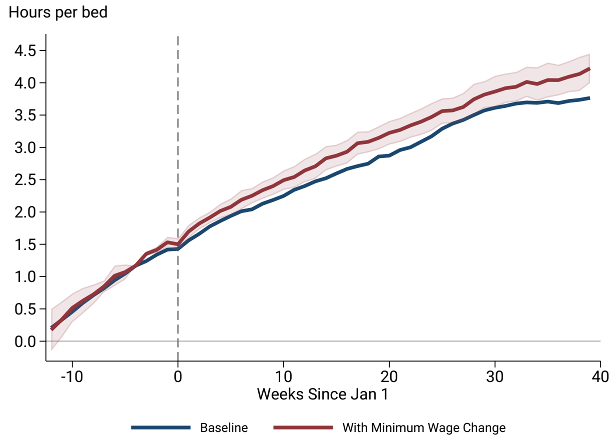
	Retained Hires	Hires				Separations			
		No Hours [0, 0]	Very Part-Time (0, 20)	Part-Time [20, 35)	Full-Time [35, ∞)	No Hours [0, 0]	Very Part-Time (0, 20)	Part-Time [20, 35)	Full-Time [35, ∞)
Panel A: 26 Weeks									
Minimum Wage	0.018	0.028	-0.014	-0.028	0.014	0.005	-0.004	-0.019	0.017
	(0.012)	(0.023)	(0.017)	(0.019)	(0.019)	(0.016)	(0.009)	(0.016)	(0.012)
Mean	0.16	0.54	0.08	0.16	0.22	0.55	0.10	0.17	0.18
Std. Dev.	0.33	0.44	0.24	0.32	0.36	0.45	0.27	0.34	0.35
Implied Representative Elasticity	1.034	0.476	-1.597	-1.582	0.579	0.089	-0.372	-1.068	0.899
Panel B: 13 Weeks									
Minimum Wage	-0.001	0.037	-0.026	-0.007	-0.004	0.017	-0.001	-0.025	0.009
	(0.013)	(0.017)	(0.009)	(0.011)	(0.011)	(0.015)	(0.011)	(0.013)	(0.011)
Mean	0.30	0.41	0.11	0.22	0.26	0.45	0.13	0.21	0.21
Std. Dev.	0.41	0.43	0.28	0.36	0.39	0.45	0.30	0.36	0.36
Implied Representative Elasticity	-0.020	0.834	-2.103	-0.314	-0.125	0.354	-0.036	-1.133	0.385
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week $\times$ Cohort	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility $\times$ FY	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	596	596	596	596	596	598	598	598	598
Facilities	3,573	3,573	3,573	3,573	3,573	3,573	3,573	3,573	3,573
Facility-Weeks	311,072	311,072	311,072	311,072	311,072	311,072	311,072	311,072	311,072

Appendix Figure A17: Hours per Bed, CNAs by Tenure

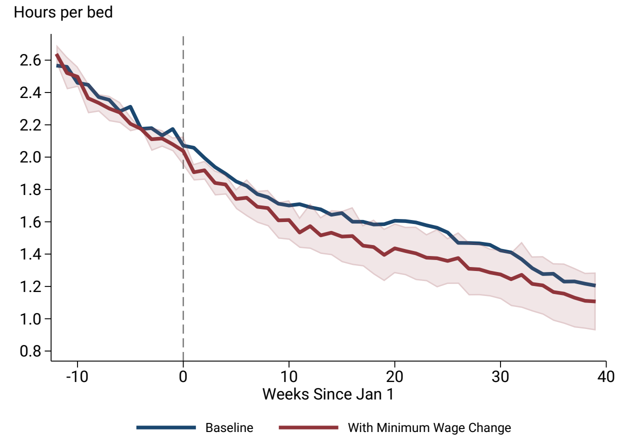


Appendix Figure A18: Dynamic Effects of Minimum Wages on Hours Worked

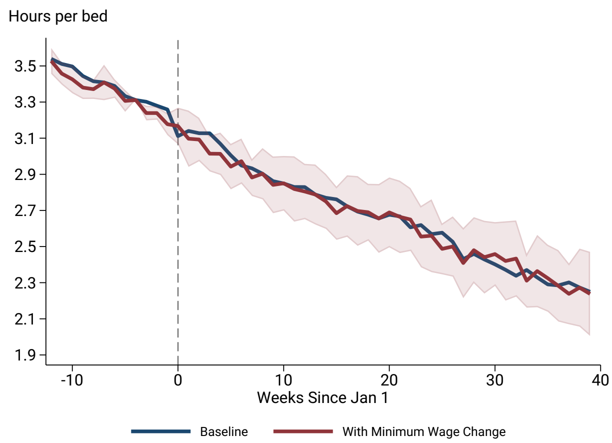
(a) New Hires



(b) 1st Tenure Tercile



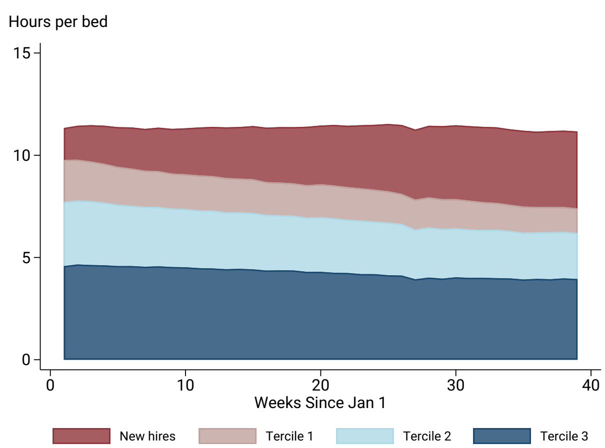
(c) 2nd Tenure Tercile



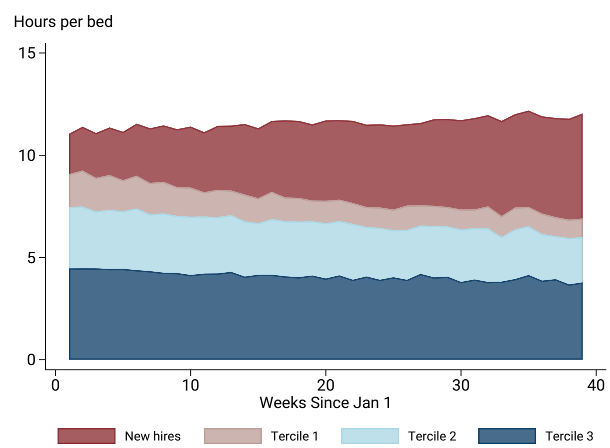
(d) 3rd Tenure Tercile

Appendix Figure A19: Overall Change in Hours Worked, by Tenure

(a) No Minimum Wage

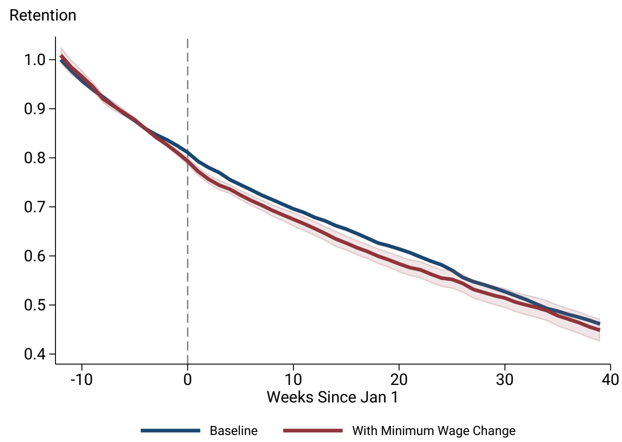


(b) Minimum Wage, Jan 2018 or Jan 2019

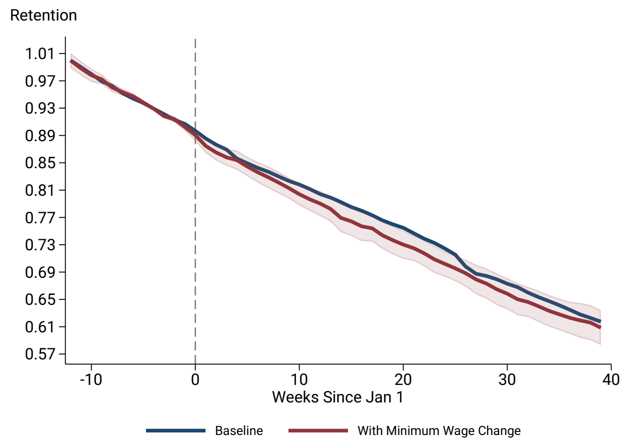


Appendix Figure A20: Retention

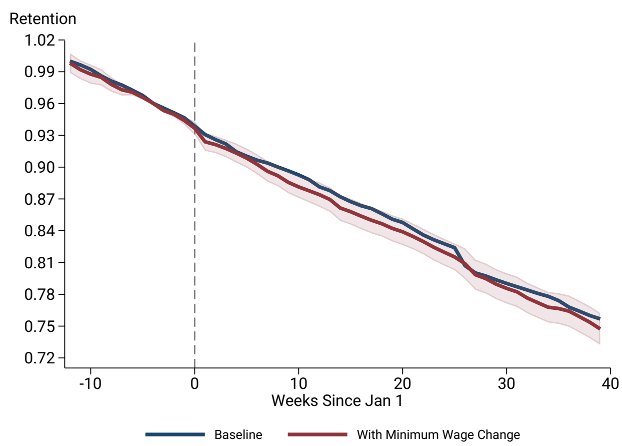
(a) 1st Tenure Tercile



(b) 2nd Tenure Tercile

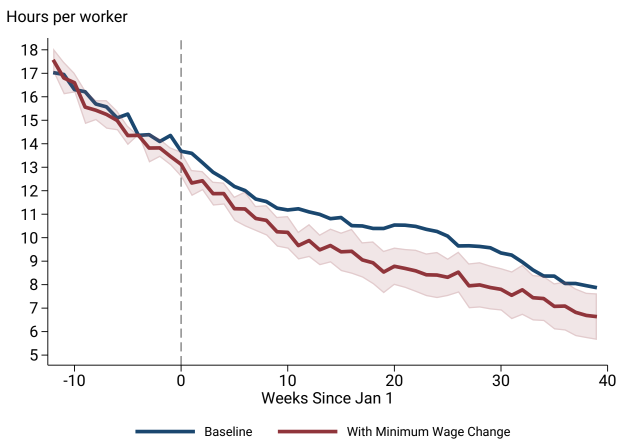


(c) 3rd Tenure Tercile

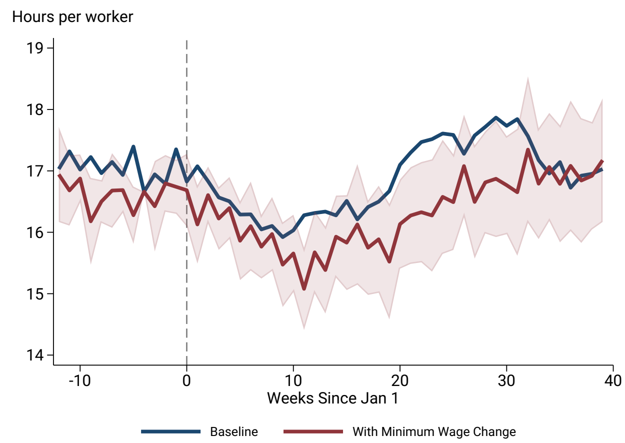


Appendix Figure A21: Changes in Hours per Worker, With and Without Changes in Retention

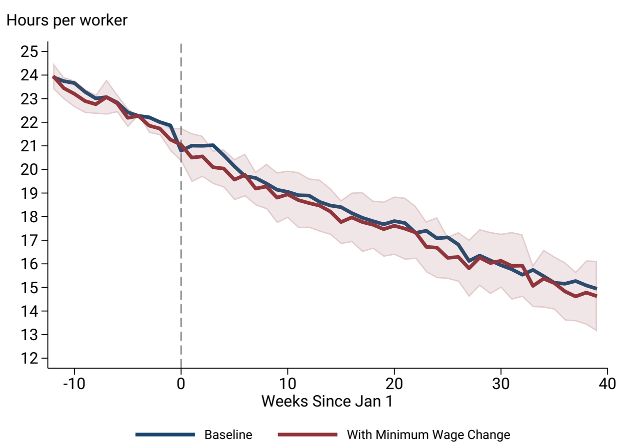
(a) Tercile 1, with Retention Effect



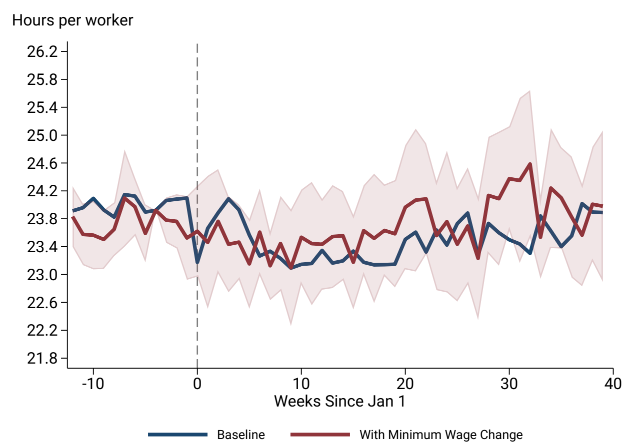
(b) Tercile 1, per Retained Worker



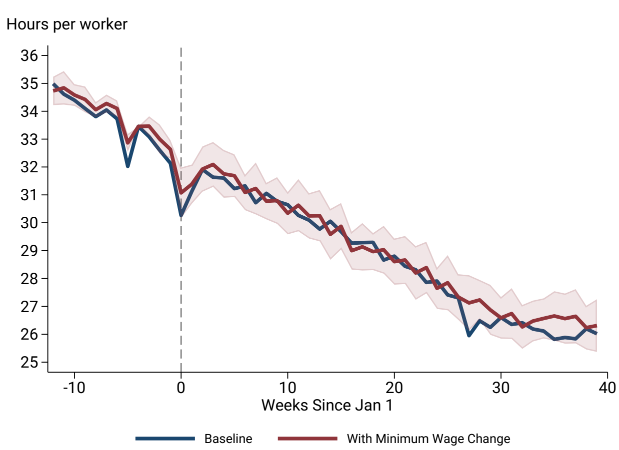
(c) Tercile 2, with Retention Effect



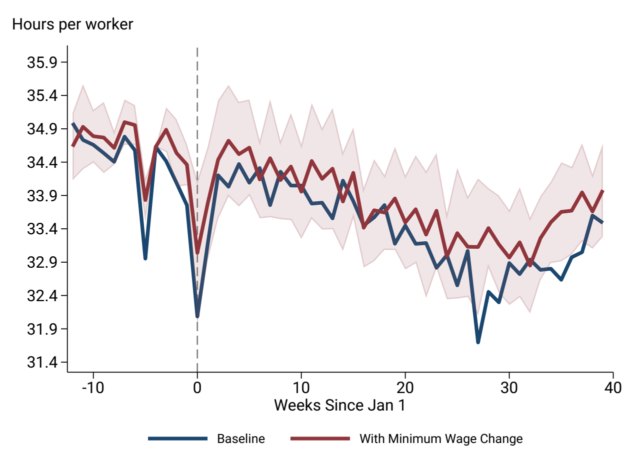
(d) Tercile 2, per Retained Worker



(e) Tercile 3, with Retention Effect

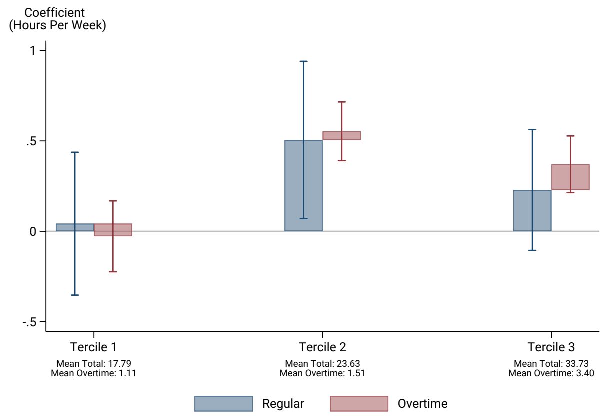


(f) Tercile 3, per Retained Worker

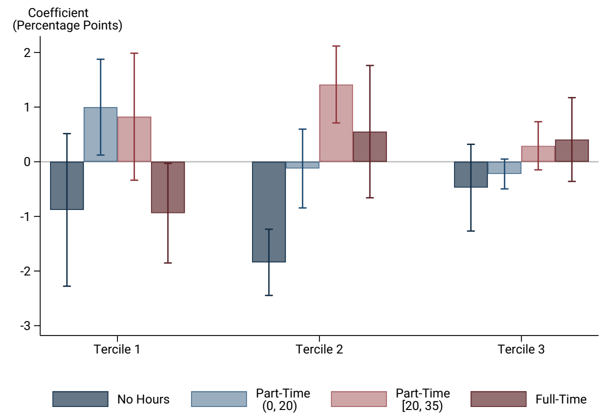


Appendix Figure A22: Characteristics of Low-Wage Work

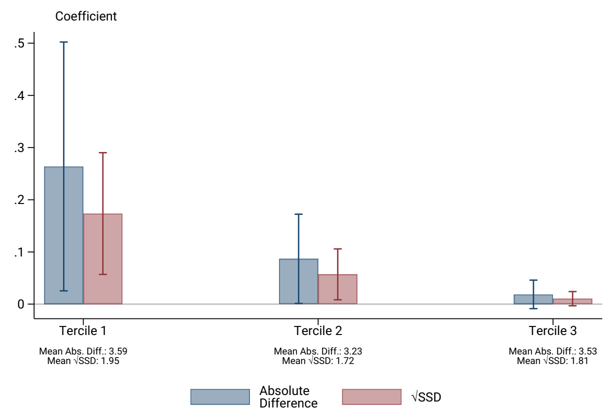
(a) Hours Per Worker



(b) Part-Time and Full-Time



(c) Scheduling Volatility



A.7 Estimates used in simulation

There are three key steps in this simulation: estimating retentions, hires, and hours. We start with the workers that are still employed at the end of our analysis sample. We then place them under two counterfactual scenarios: 1) the base case with no minimum wage increase, and 2) the treated case with minimum wage increase. In the treated case, the estimates used in simulation are obtained by adding the treatment effect coefficients - scaled by the size of the minimum wage increase - to the base case.

On the first week of each fiscal year, we begin by (re-)assigning a retention curve from Figure **??** to each worker based on the worker's tenure at the start of the fiscal year. From these estimates of workers' cumulative retention probabilities, we can compute the conditional probability of a worker being retained on week t given that the worker was retained on the previous week. For the treated case, we scale the treatment effect estimates by the size of the minimum wage increase and add to the baseline. We then draw from the Bernoulli distribution based on this conditional probability to simulate retention of each worker in payroll on week t.

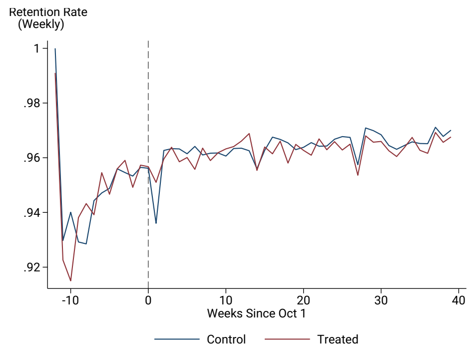
The second step is to simulate hires. We model the hiring process for each facility under each counterfactual scenario by a Poisson process, parameterized by the additional number of workers required to maintain the number of hours of care per bed each week. The number of hours of care per bed is obtained from the estimates from Figure A24 by summing across the hours of care at each level of tenure. The treatment effects are then summed across and added to the baseline sum for simulating the treated case. We next subtract the number of hours provided by the retained workers, estimated by multiplying the number of workers in each tenure group by the number of hours per worker estimates in Figure A26. Finally, we divide the resulting number of hours in deficit by the number of hours of care offered by new hires, and scale by the facility bed count to obtain the number of new hires needed to maintain the estimated weekly hours of care under each counterfactual scenario. Because we do not observe the future number of beds, and facilities are subject to constraints such as the physical space available and certificate-of-need laws, we assume that the facility bed count does not change.

The final step is to simulate the weekly working hours for each worker. We do so by first constructing an empirical distribution of working schedules over the course of each fiscal year. We construct the empirical distributions using actual workers that were in the control group in the fiscal years 2018 and 2019. Figure A25 shows the distribution of the hours on the last week of the fiscal years. We then simulate the working hours for each worker by first matching the worker to the empirical distribution on the worker's tenure level and the week of separation if the worker separated midyear. We then randomly draw a yearly schedule from the matched empirical distribution and compute tenure by cumulatively adding the weekly hours from the drawn worker's schedule. For the treated group, we use the same empirical distribution, but the minimum wage scaled treatment effects as shown in Figure A26 are subsequently added.

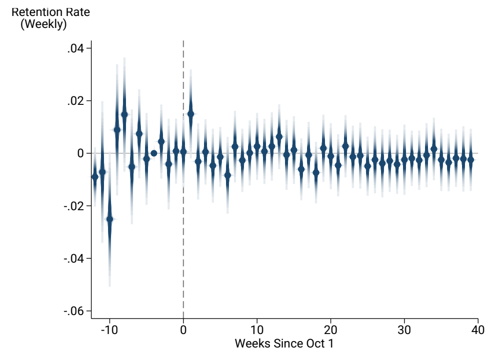
Long-run Equilibrium In order to illustrate the effect of minimum wage in the long run, we simulate pre-treatment using this procedure assuming only the base case scenario until the tenure distribution reaches an equilibrium. Once this equilibrium is reached, the tenure distribution for the base case will be stable, except for relatively minor seasonal differences within the year. This way, we can isolate the effect of minimum wage increase on the equilibrium.

Appendix Figure A23: Weekly retention rate estimates

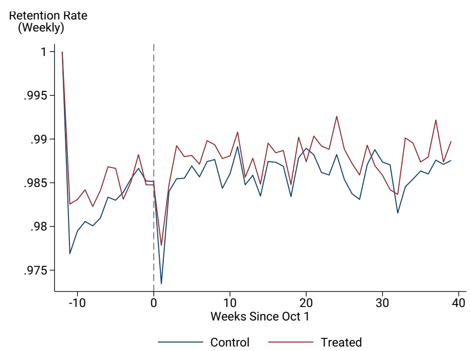
(a) New Hires



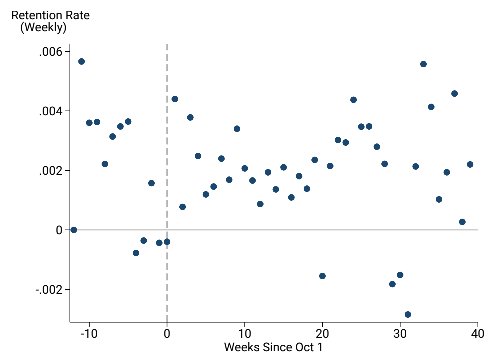
(b) Difference



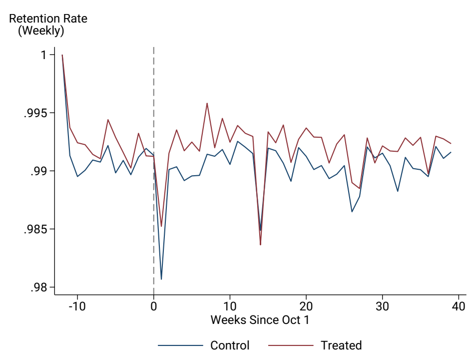
(c) Tercile 1



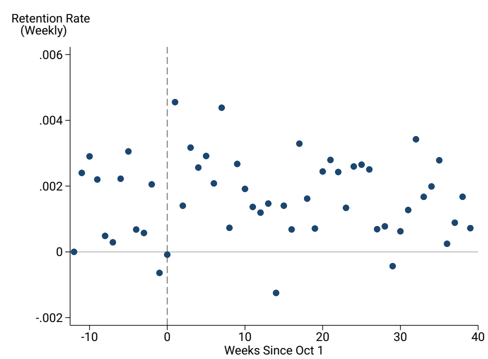
(d) Difference



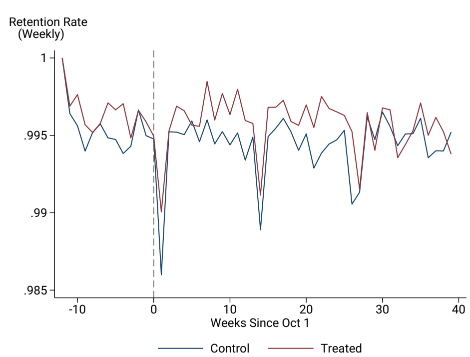
(e) Tercile 2



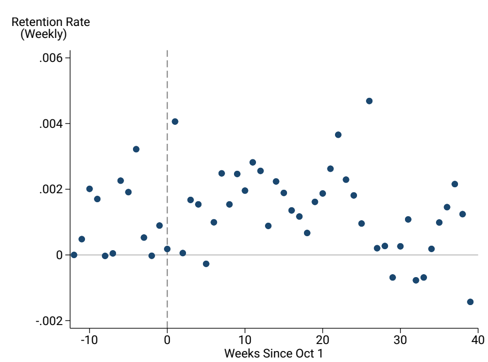
(f) Difference



(g) Tercile 3

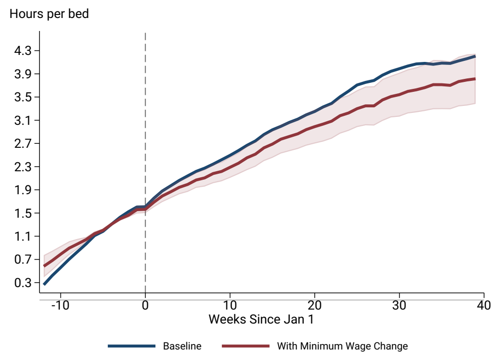


(h) Difference

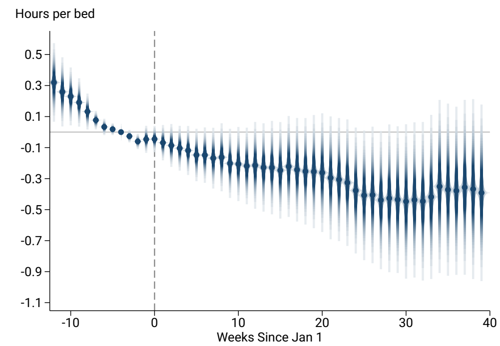


Appendix Figure A24: Hours per Bed

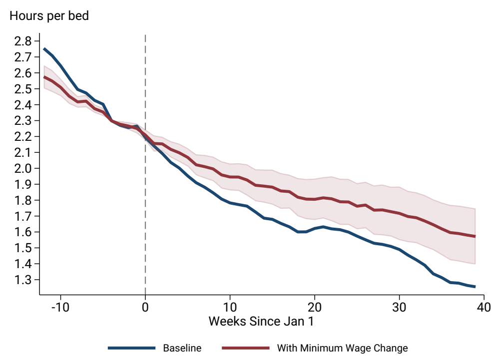
(a) New Hires



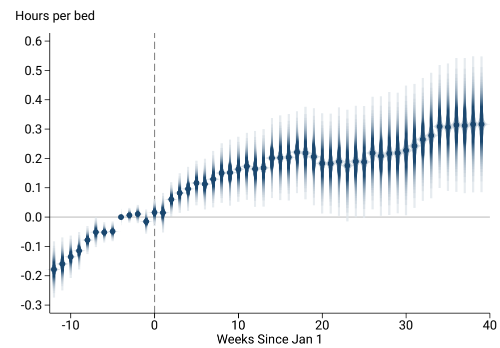
(b) Difference



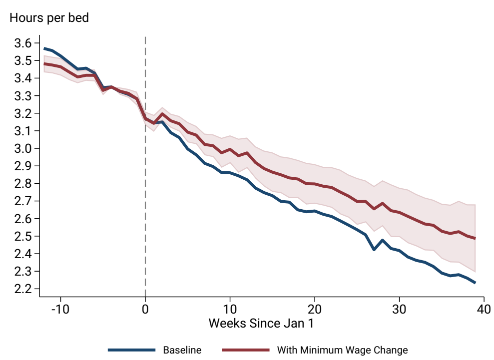
(c) Tercile 1



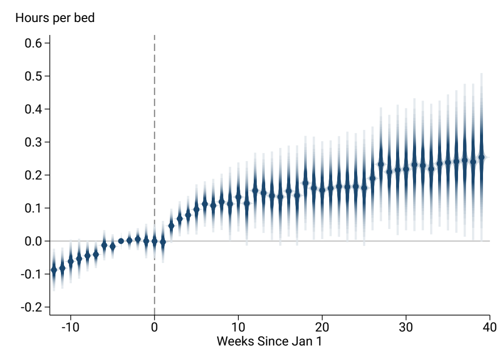
(d) Difference



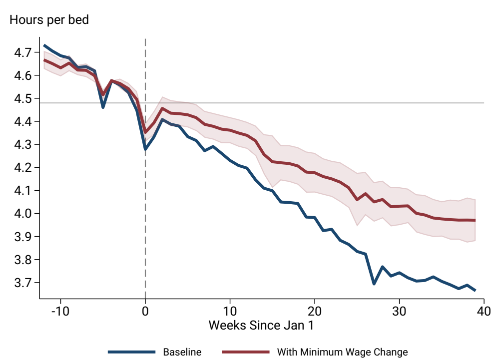
(e) Tercile 2



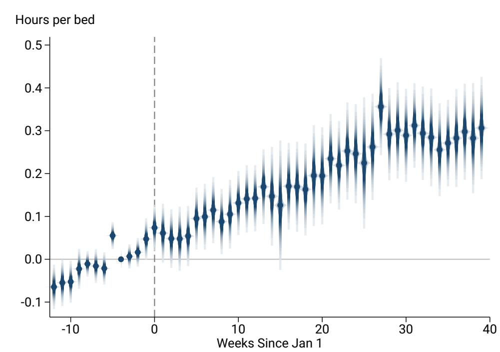
(f) Difference



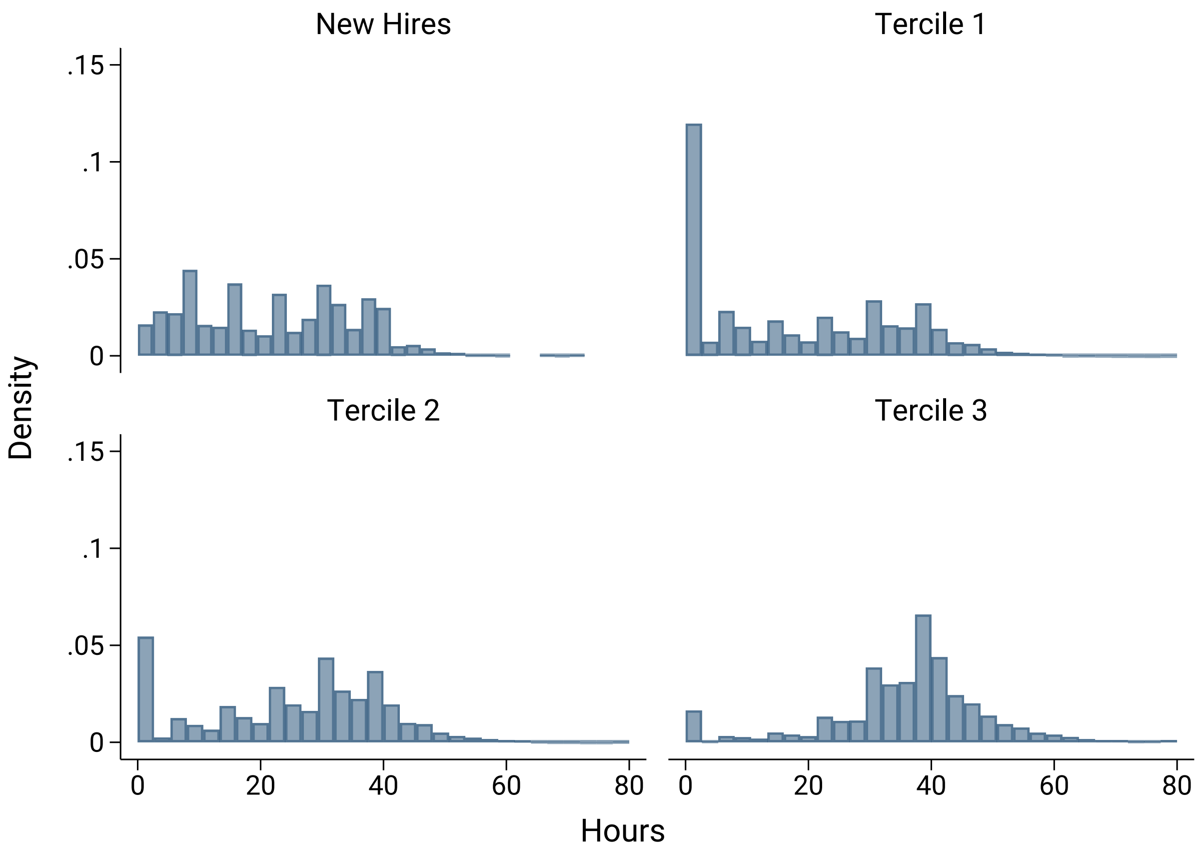
(g) Tercile 3



(h) Difference

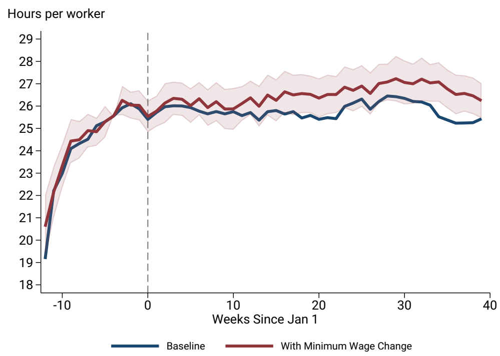


Appendix Figure A25: Empirical distribution on week 52

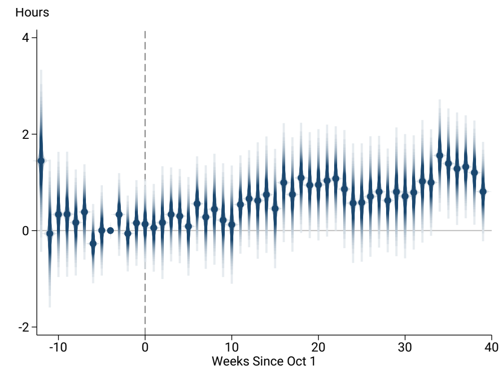


Appendix Figure A26: Hours per Worker

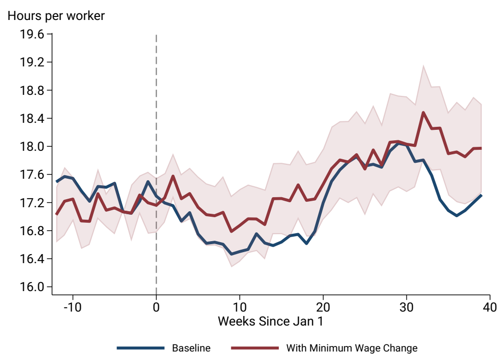
(a) New Hires



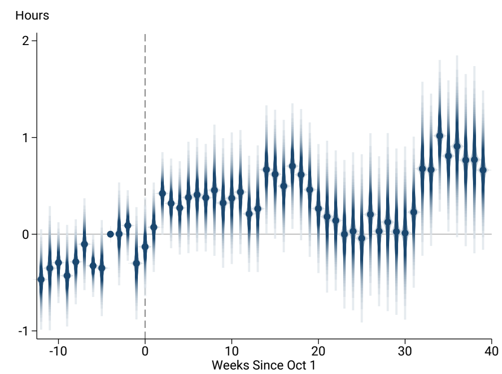
(b) Difference



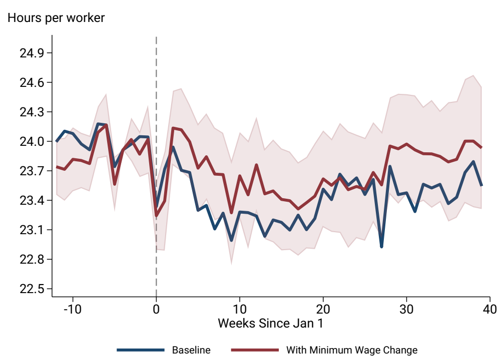
(c) Tercile 1



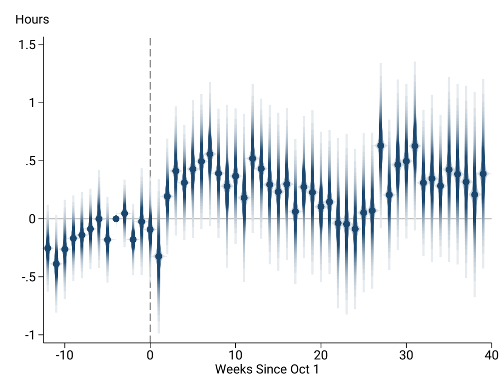
(d) Difference



(e) Tercile 2



(f) Difference



(g) Tercile 3

(h) Difference