Minimum Wages and Employment Composition*

Ashvin Gandhi[1] and Krista Ruffini[2]

[1]UCLA Anderson School of Management

[2]McCourt School of Public Policy, Georgetown University

Preliminary draft, please do not cite

Click for most recent draft

December 26, 2022

Abstract

This paper examines how minimum wages change the types of workers that firms employ and the allocation of hours across these workers. We leverage shift-level data for the universe of nursing home employees matched to more than 300 state, county, and city minimum wage changes between 2016 and 2019. We find that higher minimum wages shift the allocation of hours towards workers with high levels of firm-specific experience, driven by greater retention amongst the most experienced workers. We use our reduced-form estimates to simulate the long-term effect of a $1 increase in the minimum wage and find such a reform would increase the share of hours worked by employees with more than one year of full-time employment by 14 percent.

*We thank Lindsey Bullinger, David Grabowski, Nora Gordon, Simon Mongey, Aaron Sojourner, Melanie Wasserman, Abigail Wozniak, Román D. Zárate, Nicolas Ziebarth, and participants at Georgetown University, the Federal Reserve Bank of Minneapolis, UC-Berkeley, UN-Reno, Syracuse University, SUNY-Albany, the Northeast Labor Symposium, ASHEcon, Essen Health Conference, the Junior Health Economics Summit, KU-Leuven, Washington Center for Equitable Growth, and Stanford SITE conferences for helpful comments. Yoon Sang Moon and Yan Bo Zeng provided outstanding research assistance. We are grateful for support from the W.E. Upjohn Institute and Washington Center for Equitable Growth.

1 Introduction

Minimum wages mechanically weakly increase workers' hourly pay, but the effect on earnings is ambiguous since reductions in employment, hours worked, or non-wage compensation can offset or reverse the hourly wage gains. The net effect of employment and wages may vary by workers' occupation, experience, pre-reform income, or relative productivity. 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 and how employers allocate hours across those workers.

How the minimum wage affects different types of workers is of first-order importance in drawing conclusions about the effects of higher minimum wages from a social welfare standpoint, and such responses are crucial to have a full understanding of how government interventions shape the nature of low-wage work.

Economic theory predicts that higher minimum wages will shift the number of hours worked away from the lowest-paid workers, and this response could occur along either the extensive margin through lower hiring, or the intensive margin, through reducing hours allocated to individual workers. As a corollary, by reducing the relative cost of workers who are paid slightly more than the minimum, more experienced and incumbent workers are expected to work more, either through greater retention or each incumbent employee working additional hours.

Empirically analyzing these theoretical predictions is a data-intensive endeavor, especially in a policy environment where minimum wage changes are frequent events across space and time. In many settings, longitudinal data that tracks individual worker patterns is incomplete, non-existent, or limited to a small number of minimum wage changes. These limitations raise questions about generalizability of existing work to other settings and time periods. These concerns that become paramount as the past decade has seen a pronounced shift away from punctuated federal minimum wage reforms that substantially change the nominal minimum, towards state and local changes, many of which are more modest in size and are adjusted annually to incorporate increases in the cost of living.

In this paper, we provide some of the first empirical evidence examining how higher minimum wages affect how employers allocate hours across workers with different levels of firm-specific experience for an entire industry that was subject to hundreds of minimum wage changes over a three-year period. Using administrative, individual-level data that is reported at the daily, shift-level for the universe of US nursing home employees, we document that the effects of minimum wages vary across the experience distribution.

The richness of these administrative payroll data allow us to overcome several empirical challenges in the previous literature. First, the granularity of these data, covering more than 15,000 facilities and 700 million worker shifts over 300 state, county, and local minimum wage changes, provide nuanced insights into how minimum wages affect low-wage employment for an entire industry. Second, the data precisely measure how many hours each employee worked each day, allowing us to track new hires, separations, total hours worked, and overtime shifts on a daily basis.

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) who are paid an hourly wage, as well as the hours worked by these employees. The patterns we observe are consistent with higher minimum wages enabling firms to better retain their most experienced workers. Across nursing occupations, we do not observe any reduction in employment, nor do we find changes in occupational composition.

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 in the short-term. 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. The retention effect becomes relatively more important over time for the most experienced workers: 9 months after the higher wage is implemented, the retention component can explain essentially all of shift in the firm-level hours allocation for these workers.

Third, we examine how minimum wages affect the nature of low-wage work for individual workers, and whether these effects differ with firm-specific experience, in order to better understand how firms are able to retain their most experienced workers. In doing so, we provide some of the first empirical evidence of how higher minimum wages affect scheduling practices such as the use of overtime and week-to-week scheduling volatility. We find that the increase in hours does not significantly vary across the experience distribution. But because relatively inexperienced workers work tenuous hours before the minimum wage increase, after the higher wage becomes effective, these workers become more likely to work part-time weekly hours (versus no hours in a given week), whereas their most experienced peers transition to full-time work.

Finally, we use our reduced-form 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 4 percentage points (approximately 14 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 by individual workers. 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 precision 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 do not decrease low-wage employment, measured by the number of workers and increase the 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 turnover 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 hiring and the separations rate (Portugal and Cardoso, 2006; Dube et al., 2016; Gittings and Schmutte, 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 4 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, 2022).

Third, previous work finds that higher minimum wages reduce lower-tail inequality and poverty in the cross-section (DiNardo et al., 1996; Lee, 1999; Lemieux, 2008; Autor et al., 2016; Dube, 2019b). This reduction in income inequality combines relative changes in both hourly wages and hours worked. We focus on the hours-worked component and find that higher minimum wages prompt firms to alter the allocation of hours towards workers with high levels of firm-specific experience, consistent with studies that examine recent case-study changes (Jardim et al., 2020; Gopalan et al., 2021) or how educational requirements of entry-level jobs change (Clemens et al., 2021). We extend the existing literature by examining the dynamics of these changes at a weekly level up to nine months after a minimum wage reform and document that hours reallocation towards more experienced is due to both a retention effect and changes in the number of hours worked for individual workers. Over time, the retention effect becomes relatively more important, and after 9 months, can account for nearly all of the increased number of hours worked by the most experienced workers. In addition, we provide some of the first evidence on scheduling practices that could account for higher retention and find that for incumbent workers, schedules become more stable on a week-to-week basis and the number of weeks with zero hours worked falls.

The rest of this paper proceeds as follows. Section 2 provides background on nursing homes and minimum wages and describes the administrative data. Section 3 outlines the margins through which employers can alter the allocation of hours and describes the empirical framework used to explore this relationship. Section 4 presents results and Section 5 concludes.

2 Institutional background and data

2.1 U.S. nursing home industry

We examine the effects of higher minimum wages in the context of the US nursing home sector. 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 account for about 40 percent of all workers in the industry and provide the majority of direct care to residents. These workers typically earn low wages that 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), and previous work finds an elasticity of CNA earnings with respect to the minimum wage ranging from 0.11 to 0.33 (Ruffini, 2022).

Second, like other low-wage occupations, turnover amongst CNAs is high. When accounting for multiple employees working in the same position over the year, firm-level annual turnover rates frequently exceed 100 percent (Gandhi et al., 2021). High turnover represents an area of significant concern for the industry. In particular, CMS considers high turnover to be a key indicator of poor quality, and began featuring turnover rates as a measure of staffing quality on its consumer-facing Nursing Home Compare tool and in the five-star rating system for nursing homes beginning in 2022 (Centers for Medicare and Medicaid Services, 2022).

Previous studies that leverage cross-sectional (Castle and Engberg, 2005), panel (Loomer et al., 2022), and instrumented (Antwi and Bowblis, 2018) variation in turnover rates suggest that high turnover is associated with worse performance on numerous health inspection and resident health assessment-based metrics. Two likely mechanisms are that high turnover creates significant operational challenges for facilities (Mukamel et al., 2009; Murrin, 2021) and that low retention leads to a lack of firm-specific knowledge and expertise, which can impede the performance of workers and caregiving teams. Many nursing responsibilities rely on facility- and resident-specific knowledge. For example, proper infection control requires staff to make adjustments based on specific residents' and staff members' diseases and vulnerabilities and to follow facility-specific protocols on hygiene, equipment, and laundry. Specifically for CNAs, a primary tasks is to assist residents with activities of daily living (ADL), including eating, bathing, toileting, and mobility needs. Workers with longer facility-specific tenures have more developed relationships with residents and likely are better able to understand and address residents' individual needs, circumstances, and preferences. In a survey, current and former nursing home staff indicated that they believe that staff members with lower tenure are likely to be less efficient and provide care that is lower quality and results in more adverse outcomes for nursing home patients (Antill et al., 2022).

Third, similar to other industries, CNA wages increase modestly with each additional year of tenure. Using cost reporting data from the HCRIS, we find that workers in the third tercile of the firm-specific experience distribution earn an average of 10.9 percent more than new hires over our analysis period (see Appendix A.5 for details).[1] Since more workers with the longest tenures earn more than the newest hires, minimum wages decrease the *relative* wage of the most experienced workers compared to less-experienced workers. Accordingly, changes in the minimum wage have the potential to affect earnings inequality within this occupation.

[1]We find similar patterns examining wage and tenure data from the Survey of Income and Program Participation (SIPP), where additional year of firm-specific experience raises wages by 1.6-1.7 percent between 2013 and 2019, roughly equivalent to estimates examining returns to experience in other industries (Goldsmith and Veum, 2002). See appendix for calculation details.

2.2 Minimum wages

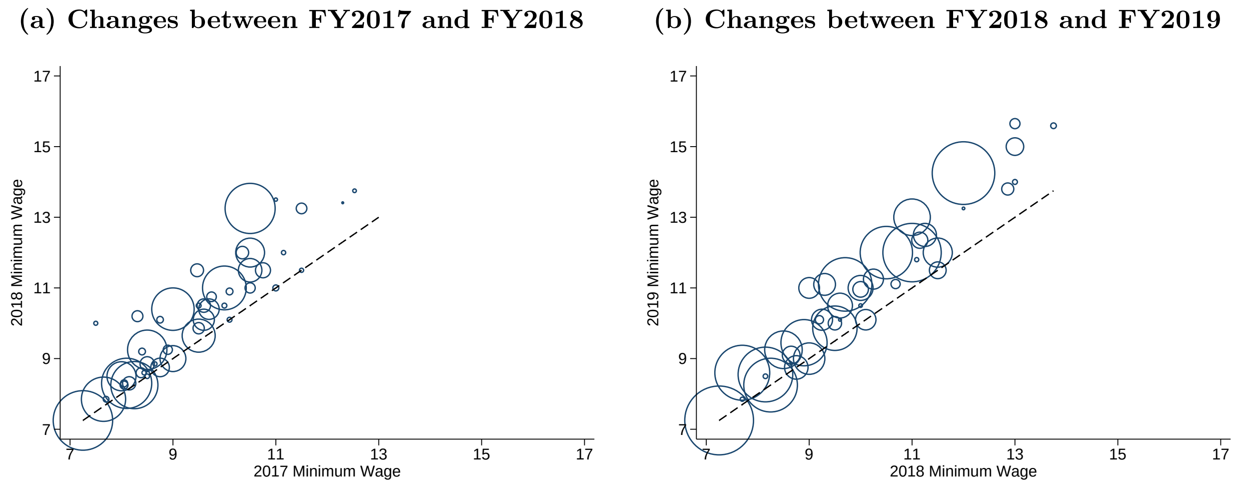
Minimum wage increases occur frequently at the federal, state, county, and city level. In addition, some jurisdictions set different minimum wages for large and small employers. We examine a period of extensive state and local action in minimum wage regulation covering federal fiscal years 2017-2019 (i.e., October 1, 2016 through September 30, 2019).

The 2016-2019 period differs from previous eras of minimum wage reforms in several respects. Throughout much of the 1990s and 2000s, minimum wage increases occurred due to legislative action at the federal or state level and were punctuated occurrences that generated relatively large changes in the nominal minimum. In contrast, over the 2016-19 period, all changes occur at the state and local level, and reforms many are annual changes intended to account for increases in the cost of living. In total over our sample period, there were 68 state, 108 county, and 128 city-level reforms, and the majority of facilities were subject to at least one minimum wage change. We match daily state, county, and city minimum wage rates for each employer size from Labor Center (2021) to administrative nursing home staffing data, described below.

Figure 1 illustrates that in addition to substantial variation in initial minimum wage levels, both areas with low and high initial minimums increased their statutory minimum wage over the analysis period, and there is substantial variation in the size of the increase. Most changes were small compared to historical minimum wage changes in the 1990s and 2000s – the largest increase in our sample is \$2.75 (approximately 20 percent). Within this sample, our analysis focuses on the subset of changes that increase the minimum wage by at least 50 cents and therefore provide meaningful changes from the previous minimum (Appendix Figure A1). This subset of reforms accounts for the majority of changes over this period. All reforms in this sample increased the statutory minimum at least 4 percent, and the typical reform increased the statutory minimum by about \$0.90 (Appendix Table A1), which is about 9% of the average.

The moderate minimum wage changes over the 2016-19 period, coupled with a modest experience wage premium, make the nursing home industry an ideal setting to examine how the composition of employment responds to changes in the minimum wage. As an illustrative example, consider a facility that starts with a minimum wage increase of \$10 and becomes subject to an \$11 wage — minimum wage levels and changes that are close to the average we observe towards the end of the sample period (Appendix Table A1). Prior to the higher minimum, suppose newly-hired CNAs are employed at a wage of \$12.24 (a representative wage that coincides with the the national

Figure 1: Minimum Wage Increases, FY17-19



Note: Figure shows the minimum wage in fiscal year t on the horizontal axis and the minimum wage in fiscal year $t+1$ on the vertical axis. The distance from the dashed 45 degree line indicates the size of the minimum wage change. Circles are minimum wage-combination specific; the radius is proportional to the number of nursing home beds in each cell.

25th percentile of CNA wages in 2019). Using data from cost reports that facilities submit to the federal government (HCRIS), we estimate a 10.9 percent experience premium between newly-hired workers and their most experienced counterparts, which yields a wage of \$13.57 for workers in the third tenure tercile. Previous work has found an elasticity of hourly wages with respect to the minimum wage of approximately 0.12 for CNAs (Ruffini, 2022) and estimates that, nationwide, about 33.6 percent of CNAs would receive a raise under a 10 percent minimum wage increase.[2] These two points in combination allow us to provide a rough estimate of how much the wage gap between new hires and experienced CNAs decreases when the minimum wage increase.

We first suppose that hourly pay is monotonically increasing in experience, consistent with the patterns we observe in the HCRIS data. Therefore, none of workers who receive a wage increase (either directly or through spillover effects) are in the top two experience terciles. The wage elasticity for these workers is zero. Scaling the wage average elasticity by the share of CNAs who receive an increase then uncovers the wage elasticity for new hires and suggests that new hire wages would increase by about 3.4 percent under a 10 percent minimum wage increase ($\epsilon = 0.115/0.336 = 0.342$).

Therefore, a \$1 (10 percent) minimum wage increase is expected to increase the wage for new

[2]These are estimated using national data from the Current Population Survey that does not include county identifiers for all respondents. Therefore, these estimates include workers in "high pay ratio" areas (Figure 3). Insofar as wages in higher-pay ratio areas change with the minimum wage, then Table 1 will understate the extent to which minimum wage increases reduce the experience premium.

hires to \$12.44, without changing wages for more experienced workers. Accordingly, a minimum wage increase reduces the wage gap between experienced and inexperienced workers from 10.9 percent to 7.2 percent (Table 1). This stylized example highlights that relatively small minimum wage changes can substantially reduce the relative cost of employing more experienced labor due to a narrow experience premium.

Table 1: Representative wage gap between new hires and experienced workers

	Wage New hires	Wage Tercile 3	Wage gap (\$)	Wage gap (%)
\$10 MW	12.24	13.57	1.33	10.9%
Earnings elasticity WRT MW	0.342	0		
After \$1 MW increase	12.66	13.57	0.91	7.2%

Notes. New hire wages estimated as the 25th percentile of CNA wages from the 2019 OES. Initial wage gap calculated as experience premium between new hires and the third experience tercile from HCRIS. Earnings elasticity 0.2 from (Ruffini, 2022) based on a \$10 initial minimum wage.

2.3 Sample Restrictions

We restrict our analysis sample in two ways. First, we exclude areas in which a single facilities has substantial labor market power in order to avoid conflating responses between employers in competitive and monopsonistic labor markets. Second, we restrict our sample to facilities located in markets where typical CNA wages are low relative to the minimum wage, since these are the markets in which minimum wage increases are most likely to bind. We describe each of these restrictions in greater detail below.

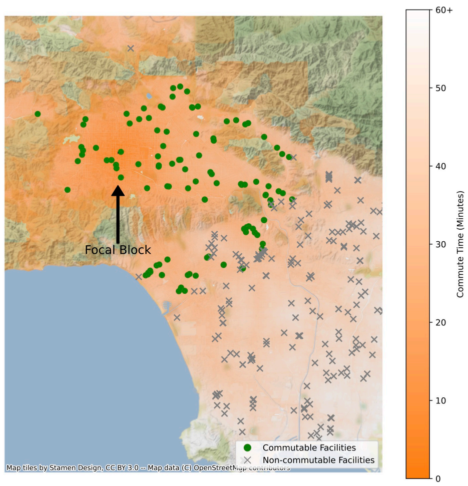
Labor market power We identify facilities unlikely to have substantial monopsony power based on a HHI-based measure of labor market concentration. This measure is based on commuting times, since all else equal, workers prefer workplaces with shorter commute times (Small et al., 2007).

We first compute the 75th percentile driving commute time for workers in the health care and social assistance industries in each commuting zone by using Census Bureau LEHD Origin-Destination Employment Statistics (LODES) data to identify census blocks where health care employees live (Shen, 2020).

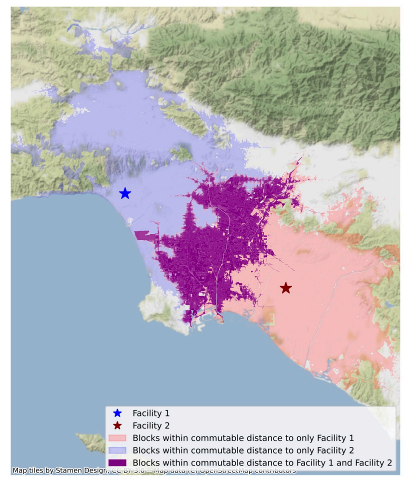
We then compute a block-level labor market Herfindahl-Hirschman Index (HHI) for each census block, assuming that the most relevant "commutable" facilities competing for labor in that block are those within a 75th percentile commute time from each worker's residence. Figure 2a illustrates this approach to determining for an example census block in the Reseda neighborhood of Los Angeles. The shaded heatmap (panel a) gives the commute time from that census block to the other 143,747 blocks within a 80km radius. The green circles represent commutable facilities from that block, which are the facilities incorporated into the block-level HHI.

Figure 2: Measuring labor market HHI

(a) Commutable Facilities



(b) Local Competition for Workers



Note: Figure 2a shows the driving time from the focal block in Reseda (Los Angeles metropolitan area) to nearby blocks. All the nursing homes within the typical commute distance (measured as the 75th percentile of driving time) are marked in green, representing the employment options for a worker living in this block.
Figure 2b shows the unions of blocks that can reach either of the two example facilities in Westwood, CA and Anaheim, CA. These represent the areas for which the block-level HHI is aggregated to the facility-level.

Under this approach, any two facilities may be competing over labor in some residential blocks but not in others. Figure 2b shows this through the partially-overlapping labor markets of two facilities in Los Angeles. Since facilities face varying degrees of labor market competition for workers that reside in each block, we measure a facility's labor market power using the population-weighted average HHI of the census blocks from which the facility is commutable. Our main results focus on facilities that face an average labor market concentration lower than 0.2, which is approximately the 80th percentile (Appendix Figure A2). A representative example of a market with an HHI of 0.2 is one in which five identical facilities have an equal labor market share. [3]

Low-pay areas Minimum wage increases are most likely to affect CNA wages in places where the prevailing CNA wage is close to the minimum wage. Although our staffing data has rich information on hours worked at the individual level, these data do not report wages. Therefore,

[3] Appendix A.4 provides additional details on these calculations.

we rely on wage data from the Quarterly Census on Employment and Wages (QCEW) and the Occupational Employment Statistics (OES) to identify areas where minimum wages are most likely to be binding for nursing home workers.

For each facility, we compute a measure of how many weekly hours of work at the statutory minimum wage are required to receive CNA pay typical for the county. We refer to this measure as a "pay ratio" since it the ratio between the average CNA wage in the county and the local minimum wage. Formally, the pay ratio for facility i in county c during quarter t is:

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

where $\overline{CNAwage}_{ct}$ is the average weekly wage for CNAs computed using the QCEW and OES data, and MW_{it} is the statutory minimum wage faced by facility i at time t.[4]

The pay ratio provides an intuitive measure of how "binding" a minimum wage is likely to be. A *low* pay ratio indicates that a facility is in an area where CNAs earn wages close to the minimum and increases in the minimum are expected to raise pay for nursing home workers. It is important to emphasize that a low pay ratio does not necessarily imply that CNA wages in the area are low on an absolute scale; rather, a low pay ratio indicates that CNA wages are low relative to the minimum wage. In fact, many facilities with low pay ratios are in high-wage areas that also have very high minimum wages.

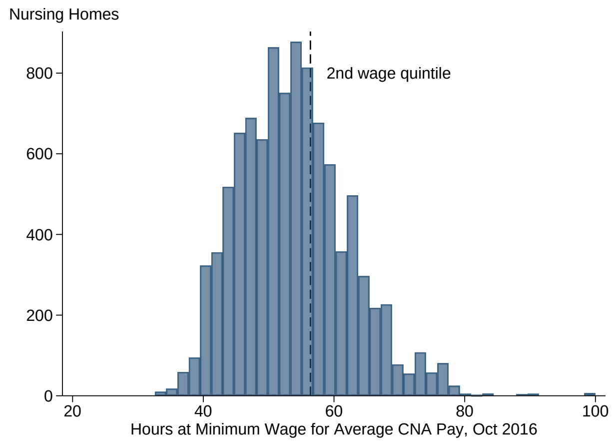
Figure 3 shows the full pay ratio distribution across facilities. We focus on facilities that are in areas in the bottom 40 percent of the county-level CNA pay ratio distribution in the first quarter of each fiscal year. In this sample, nearly all representative workers—employees receiving the typical pay for a CNA and working 40 hours a week—are expected to see their wages increase by a minimum wage change of the magnitude we study, either because they earn less than the new

[4]CNA-specific wages are not published at the county level. We do not use the firm-level staffing data reported in the HCRIS cost reports as these data are not subject to audit and are especially prone to misreporting and measurement error. See Sacarny (2018) for reporting issues with the HCRIS. The QCEW data are more reliable, as they are directly derived from UI filings firms are required to submit, albeit these are only available at the county level and provide a industry-wide measure of average weekly earnings for each county. In order to approximate CNA wages, we scale the average nursing home wage in the QCEW by the average CNA wages in the national OES data that year y for interpretability. Therefore, $\overline{CNAwage}_{ct}$ is calculated as:

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

In counties 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.

Figure 3: Pay Ratio Distribution



Note: Pay ratio 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.

statutory minimum or because they earn slightly more than the new minimum and experience a wage increase due to spillover effects.[5]

2.4 Measuring nursing home employment

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 changed staffing in the industry (Shen et al., 2022).[6]

The richness of these administrative payroll data allow 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, total hours worked, and overtime shifts on a daily basis.

[5]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). Urban areas are more likely to have low relative nursing home pay, therefore our sample includes more than 40 percent of all facilities.

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

Second, facilities typically export their submission to CMS directly from time and attendance software in order to reduce errors and audit risk.[7] As a result, reported hours are likely to be both accurate and precise. Importantly, this 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. Figures 4a and 4b respectively show the full distribution of daily and weekly hours worked by CNAs who were paid an hourly wage in federal fiscal year 2019. While there are spikes at standard half-hour shift-lengths, like 7.5 and 8 hours, 58 percent of shifts do not end on a half-hour.[8] In contrast, approximately 40 percent of nursing assistants report working exactly 40 hours a week in the ACS and CPS data.

Figures 4a and 4b also illustrate 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 changes.

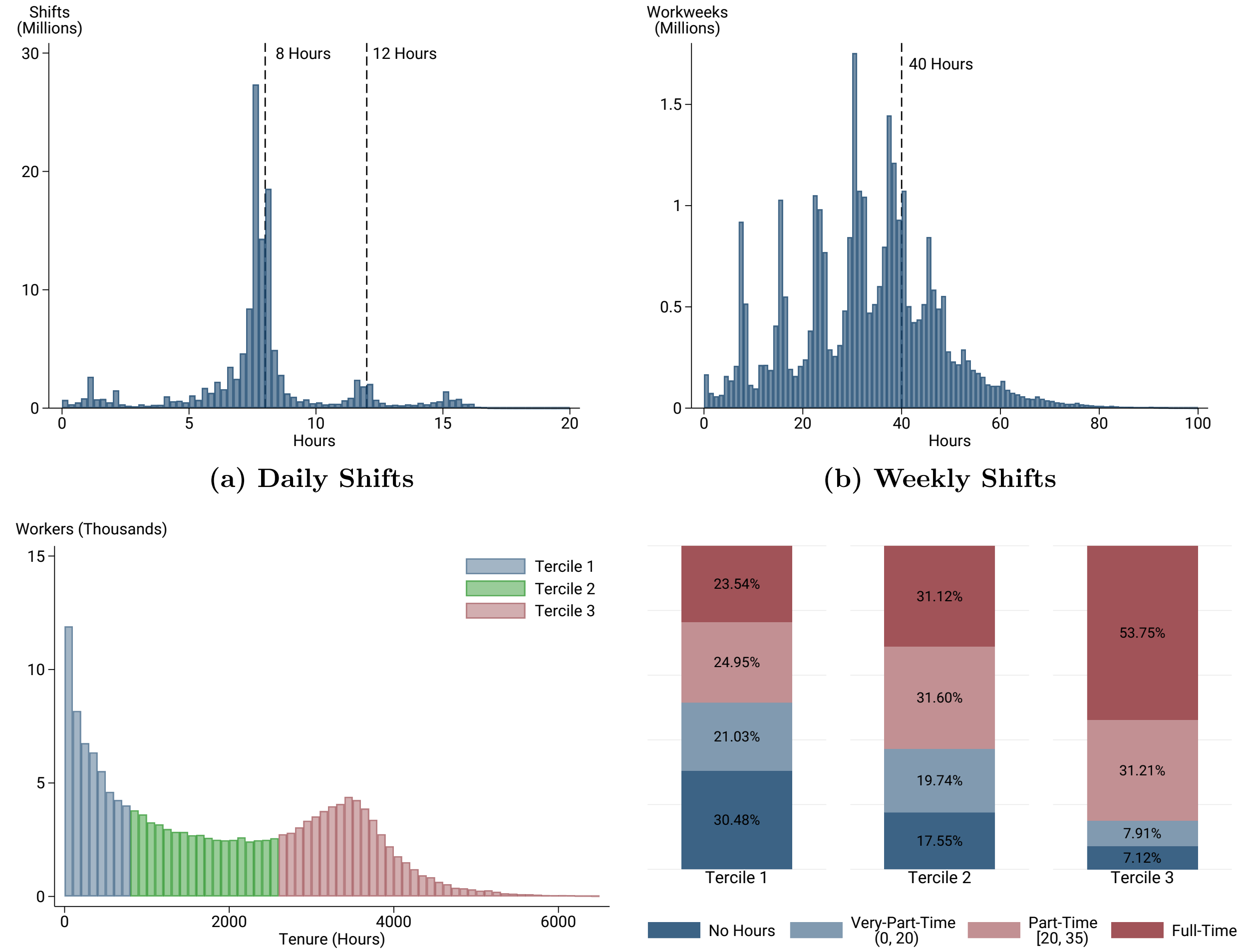
Finally, we leverage the individual-level nature of the PBJ data to track how higher minimum wages affect different types of workers. We distinguish workers based on their level of experience, measured using the total number of firm-specific hours accrued by the worker prior to the start of the fiscal 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.

Figure 4c shows the distribution of firm-specific experience for all workers in our sample at the start of fiscal year 2019. On one hand, it illustrates high rates of turnover in this setting: one-third

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

[8] 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 4: Certified Nursing Assistant Shifts and Tenure



(a) Daily Shifts **(b) Weekly Shifts**

(c) Tenure at Start of Fiscal Year **(d) Weekly Shifts by Tenure Tercile**

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

of workers have less than 761 hours of tenure (approximately 4.5 months of full-time work). On the other hand, it also shows that a large fraction of workers – those in the top tercile, do have substantial tenure with their employer. Figure 4d shows that the composition of weekly shifts varies substantially by tercile of tenure. Most notably, more tenured workers are much more likely to be working full-time and are much less likely to have weeks with few or no hours.

Table 2 presents summary statistics for our main analysis sample. Consistent with Figure 4d, the least experienced workers work fewer hours and fewer overtime hours than their more experienced co-workers in each fiscal year. Across all experience groups, nursing assistants provide about 13 hours of care per bed each week.

Table 2: Summary Statistics

	New Hires		Tercile 1		Tercile 2		Tercile 3	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Fiscal Year 2018 (2,761 Facilities)								
Hours Per Bed	3.07	2.66	1.90	1.57	3.22	2.32	4.92	3.13
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	0.17	0.24	0.44	0.46
Share of Full-Time Workers	0.33	0.22	0.21	0.19	0.30	0.19	0.56	0.20
Share of Workers with Overtime Hours	0.21	0.21	0.14	0.17	0.19	0.19	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 (2,994 Facilities)								
Hours Per Bed	2.90	2.87	2.09	1.86	3.11	2.04	5.07	3.20
Number of Workers Per Bed	0.10	0.10	0.08	0.07	0.11	0.07	0.14	0.09
Overtime Hours Per Bed	0.18	0.27	0.13	0.20	0.20	0.26	0.47	0.51
Share of Full-Time Workers	0.33	0.22	0.25	0.19	0.31	0.19	0.53	0.19
Share of Workers with Overtime Hours	0.22	0.22	0.18	0.19	0.22	0.20	0.37	0.22
Tenure Range (Hours at Start of Fiscal Year)	[0, 0]		(0, 761]		(761, 2616]		(2616, 8978]	

Notes. Data from PBJ fiscal years 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 ratio 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.

3 Conceptual framework and empirical approach

3.1 Conceptual framework

Statutory minimum wages impose a wage floor that mechanically raises hourly pay for the lowest-wage workers, who would otherwise likely earn below the statutory minimum. Increases to the minimum wage lift this wage floor, further buoying wages for the lowest-wage workers who receive wages at or just above the minimum. As the wages of these lowest-wage workers increase with the binding wage floor, the relative cost of other factors of production falls. These other inputs include capital and higher-wage labor, including highly-skilled, highly-certified, or highly-tenured workers. Therefore, employers may respond to minimum wage increases by reducing employment of their lowest-wage workers towards and shifting towards capital or higher-wage labor.[9]

In the nursing home industry, the workers earning closest to the minimum wage—and therefore the most likely to see their wages increase—are new and recently hired CNAs with little experience. Given the nature of nursing home care, the most plausible substitute for these inexperienced CNAs

[9]From the worker's perspective, increases in the minimum wage increase the opportunity cost of non-employment. In standard search and matching models (Acemoglu, 2001; Flinn, 2006), higher minimum wages can increase search effort and improve match quality between workers and firms. If the surplus from these new matches is sufficiently high, low-wage hiring may not decrease and could increase. Although this is a theoretical possibility, we focus on the labor demand side, as previous work and our empirical results show low-wage hiring falls in response to a higher minimum wage (Brochu and Green, 2013; Portugal and Cardoso, 2006; Gittings and Schmutte, 2016; Dube et al., 2016).

are more experienced CNAs. In particular, nursing home care is very labor-intensive and leaves little room to replace labor with capital. Likewise, more highly certified nursing staff—licensed practical nurses and registered nurses (LPNs and RNs)—are poor substitutes as they perform different job functions. For example, ONET task descriptions highlight that CNAs help residents with physical activities of daily living—including eating, bathing, mobility and toileting—clean resident rooms, and communicate basic information with family members, whereas LPNs administer IVs and other basic medical treatment, prepare treatment rooms, and supervise CNAs, and RNs develop treatment plans, administer medical treatment, and interpret medical results.

When the statutory minimum wage increases, nursing homes are therefore expected to substitute their input mix away from newly and recently-hired CNAs towards incumbent CNAs with greater firm-specific human capital. That is, because while experienced CNAs do command higher wages, that experience premium is likely to shrink as inexperienced CNA wages increase with the minimum wage. As we describe below, this shift could occur on either the extensive (retention) or the intensive (hours) margin.[10]

Extensive Margin ("Retention Effect"): Higher minimum wages could affect the total number of workers facilities employ in each occupation and experience category. These changes can occur either due to changes in hiring or separations. We refer to this as the "retention effect," as we find that the primary extensive-margin response in the nursing home setting is increased retention of highly tenured staff.

Intensive Margin ("Hours Effect"): Firms may also adjust the number of hours that individual employees work. For example, facilities may respond to a binding minimum wage by allocating additional hours to each of their most-tenured workers while reducing the number of hours allocated to each more recent hire.

Finally, it's worth noting that either or both of the extensive and intensive margin effects may differ by occupation or the level of worker experience. Heterogeneous responses across occupations or experience categories can lead to bifurcations in the hours and employment distribution among

[10] Responses on the extensive and intensive section could interact. 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. Since worker preferences are likely heterogeneous across (unobservable) worker types, we focus the analyses to the direct retention and hours 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.

low-wage workers that would be missed by examining the average treatment effect for all workers, as is common in much of the literature. A unique advantage to our setting is that we can distinguish the extensive and intensive margin effects, both overall and for workers of different occupations and experience levels.

3.2 Empirical approach

Our empirical approach leverages the rich variation in the minimum wage across facilities over time in a difference-in-differences design. This general approach follows much of the existing minimum wage research, but we leverage recent advances in the econometric literature in order to more fully account for reforms that occur at different times and treatment effects that may evolve over time.

In particular, minimum wage changes do not occur at the same time in all jurisdictions: two-thirds of facilities experiencing a minimum wage change in our sample do so in January while the other third experience changes in July. In such "staggered treatment designs" in which units are treated at different points in time, a traditional two-way fixed effects estimator implicitly compares newly-treated facilities to both never-treated and recently-treated facilities. The comparison to recently-treated facilities can lead to estimated effects that are of the incorrect magnitude or sign if treatment effects evolve over time (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021).

In order to exclude comparisons to facilities that were treated earlier in the year with newly-treated facilities, we adopt the group-time average treatment (ATT-GT) estimator proposed by Callaway and Sant'Anna (2021). This estimator restricts comparisons of facilities experiencing a minimum wage only to those that did not experience any minimum wage change that fiscal year. We perform our comparisons within a fiscal year in order to leverage multiple minimum wage changes faced by a single facility over the 2016 through 2019 period. This approach is consistent with the policy environment and the frequency of minimum wages, many of which are annual updates. When interpreting our results, it is important to note that our reduced-form estimates should be viewed as short-term responses that evaluate the effect of higher minimum wages up to 9 months after implementation. We address how one might generalize these results to the longer-term in Section 4.4

To construct the ATT-GT estimator, we subset the data into treatment "cohorts" based on the first week of the fiscal year in which each facility experienced a minimum wage change of at least 50 cents. We denote each cohort of facilities treated on week g by G_g. The facilities that never experience a minimum wage change that fiscal year form the control group, "C". The 50 cent treatment threshold corresponds to a minimum wage increase of at least 4 percent. In this sample, the largest increase is \$2 (20 percent) and the average is 90 cents. While this subset includes only the largest reforms in the recent years, when comparing our results with findings from earlier research, it is important to note that these changes are relatively small compared to historical changes, particularly those enacted at the federal level.[11] We estimate the difference in outcome Y between each treated cohort G_g and the control group for each week $t \in T$ between October 1, 2016 and September 30, 2019:

$$Y = \alpha_1^{g,t} + \alpha_2^{g,t}\mathbb{1}(T = t) + \beta^{g,t}(\mathbb{1}(G = g) * \mathbb{1}(T = t)) + \varepsilon^{g,t} \tag{3}$$

In Equation 3, $\beta^{g,t}$ corresponds to a standard difference-in-differences estimator from a setting where there are two time periods and a single treatment group. In staggered treatment designs with multiple periods, there is one $\beta^{g,t}$ for each treatment cohort and "after" period. Accordingly,we then aggregate $\{\beta^{g,t}\}$s from Equation 3 to form two estimators that are akin to the standard differences-in-differences "after" estimator, θ_{DD}, and event study coefficients θ_{ES}:

Overall ATT-GT (average $\beta^{g,t}$):

$$\theta_{DD} = \left(\sum_{g \in G}\sum_{t=2}^{T}\mathbb{1}(t \geq g)P(G = g|G \leq T)\right)^{-1}\sum_{g \in G}\sum_{t=2}^{T}\mathbb{1}(t \geq g)\beta^{g,t}P(G = g|G \leq T) \tag{4}$$

Dynamic ATT-GT (event time $\beta^{g,t}$):

$$\theta_{ES} = \sum_{g \in G}\mathbb{1}(g + e^{'} \leq T)\beta^{g,g+e}P(G = g|G \leq T) \tag{5}$$

The ATT-GT approach circumvents many issues that arise in standard TWFE designs; however, it does not permit a continuous treatment. Therefore, these estimates should be interpreted as the average treatment effect of undergoing a minimum increase of at least 50 cents, rather than the average causal response parameter associated with a marginal change in the minimum wage (Callaway et al., 2021). In our setting, however, the advantages of the ATT-GT approach outweigh these costs as over the 2016 through 2019 period, the variation in the size of minimum wage changes was relatively muted: 65 percent of the minimum wage increases we leverage increased the minimum

[11] Approximately 37 (2017), 36 (2018), and 13 (2019) percent of facilities experienced a minimum wage change between 5 cents and 50 cents. These observations are omitted from the analysis. Appendix Figure A1 provides a histogram of all minimum wage changes over the analysis period.

by 6-10 percent. In order to ease interpretability, all tables scale the treatment effect coefficient into an implied elasticity by calculating the average percentage change in the outcome based on pre-minimum wage levels and the average percentage change in the minimum wage for each facility that undergoes a minimum wage change. The appendix presents the results under these standard TWFE approach and shows qualitatively similar patterns, albeit where the intensive margin effect has a slightly greater role.

4 The Effect of Minimum Wages in Competitive Labor Markets

In this section, we study the impact of minimum wage increases in competitive labor markets.

4.1 Effect on Employment Levels

Relatively little is known about how minimum wages affect employment patterns among different types of workers within an industry on a national scale. Moreover, many existing studies rely on self-reported estimates of hours worked and yield imprecise results that cannot rule out sizeable increases or decreases in employment. In addition, there is limited evidence of how increases in the minimum wage affect healthcare support staff in the United States, despite the prevalence of low wages in this sector.

Before disaggregating any changes in the overall allocation of hours within a facility across worker of different types, Table 3 provides a high-level indication of how minimum wages affect aggregate employment across different occupations in the nursing home sector, measured as hours worked per bed and the number of staff on payroll. These results help benchmark the nursing home sector to other low-wage settings that have received more attention in the existing literature such as the retail and food services industry. They also help inform the extent to which the findings in earlier studies are prone to attenuation bias from measurement error in measures of hours worked.

Since facilities vary in size—the tenth percentile facility in our sample has 49 beds, whereas ninetieth percentile facility has 177 beds—we normalize both measures of employment — hours worked (panel a) and number of staff (panel b) — by the number of certified beds in the facility and weight observations by the number of certified beds. These "per bed" outcome measures therefore reflect changes in employment relative to the productive capacity of a facility.

Hours worked per bed (panel a) captures both the intensive and extensive margins of employment. Under this measure, the number of hours among CNAs who are paid hourly increases by

Table 3: 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	0.165	0.045	-0.002	0.032	0.012	0.003
	(0.085)	(0.038)	(0.019)	(0.041)	(0.033)	(0.003)
Mean	14.33	0.35	0.07	5.04	3.33	0.87
Std. Dev.	3.57	1.10	0.91	2.64	3.07	0.12
Implied Representative Elasticity	0.172	1.915	-0.355	0.095	0.055	0.052
Panel b: Weekly Number of Workers Per Bed						
Minimum Wage	-0.001	0.004	-0.001	0.001	0.000	
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	
Mean	0.55	0.04	0.00	0.18	0.15	
Std. Dev.	0.19	0.10	0.03	0.11	0.27	
Implied Representative Elasticity	-0.040	1.582	-4.009	0.113	0.034	
County Clusters	305	305	305	305	305	305
Facilities	1,472	1,472	1,472	1,472	1,472	1,472
Facility-Weeks	76,123	76,123	76,123	76,123	76,123	76,123

Notes. Table shows weekly hours per bed (panel a) and number of workers per bed (panel b) for fiscal years 2017 through 2019 under the approach in Equation 3. Time unit is at the weekly level; treated unit is the facility-by- fiscal year. All specifications weighted by the number of certified beds. Standard errors clustered by county in parentheses.

approximately 13 minutes a week following a minimum wage increase. We convert this response into a representative elasticity by scaling the point estimate by the average weekly amount of care and size of the wage increase, which implies that a 10 percent minimum wage increase would increase hours worked by CNAs paid an hourly wage by approximately 1.7 percent.

Panel b isolates the employment responses along the extensive margin by considering the number of workers on payroll per bed.[12] These results indicate that this overall increase in hours is due exclusively to an intensive margin response (number of hours per worker): an increase in the minimum wage does not significantly change the number of workers employed at a facility.

Overall, our results suggest small but positive employment effects for CNAs. These findings corroborate conclusions in other industries and settings (Doucouliagos and Stanley, 2009; Dube, 2019b), as well as earlier periods for the nursing home industry (Ruffini, 2022). The similarities with the existing literature are noteworthy not only because we consider a different industry (healthcare support) and time period (where recurrent state and local changes were commonplace), but also as our employment measure is an auditable and high-frequency measure of hours worked. Importantly, these data allow for precise measurement of employment, avoiding concerns about attenuation bias that are common in the existing literature.

[12] Workers are considered "on payroll" at a facility between their first and last week working at the facility.

In contrast to the hours gains observed for wage CNAs, we do not observe notable changes in the employment of other types of workers under either measure of employment. Most notably, we do not find evidence that higher minimum wages significantly affect the employment of credentialed nursing staff (LPNs and RNs) who earn higher wages and perform tasks that are substantially different from CNAs, such as administering more specialized medical care.[13] The lack of substitution towards other occupations indicates that the minimum wage operates primarily through affecting the CNA employees paid an hourly wage. Correspondingly, we focus on these workers for the remainder of the paper.

The final column of Table 3 indicates that minimum wage increases do not substantively change occupancy rates. Therefore, the effects we measure represent changes in the quantity and composition of inputs (workers) rather than the quantity of output (resident-days). An important implication of this pattern is that such changes to per-resident staffing likely represent changes to quality of care that can affect patient health outcomes (Friedrich and Hackmann, 2021).

4.2 Effect on Hours Allocation by Worker Experience

Table 3 measures firm-level changes in employment across occupations but may mask important heterogeneity in how minimum wages affect different types of workers within the same occupation. Even within an occupation, employees differ on a multitude of dimensions that affect their productivity. One particularly important dimension that is correlated with performance is firm-specific experience. Firm-specific experience—i.e., an employee's tenure at a firm—is generally of interest to both employers concerned about and policymakers cognizant of social welfare considerations.

In the nursing home sector specifically, tenure is important for several reasons. First, many job responsibilities, such as adhering to facility-specific protocols on infection control, rely on facility-specific knowledge. Nursing tasks also can benefit from establishing long-term relationships with residents, through which staff are able to better help residents with activities of daily living and monitor health conditions. When surveyed, nursing home staff typically indicate that tenure is important for quality of care, that less-tenured staff are less efficient, and that care provided by low-tenure staff is more likely to result in adverse outcomes for residents (Antill et al., 2022). Likewise, empirical studies leveraging both across- and within-facility variation find that higher turnover—and correspondingly more low-tenure staff—is associated with lower quality of care (Castle and

[13]Likewise, we do not estimate a significant change in the employment of CNAs that are salaried or are employed through a contract agency. However, since few CNAs are contract or salaried employees, these estimates are imprecise.

Engberg, 2005; Castle et al., 2007; Loomer et al., 2022). Second, widespread rates of low-tenure represent high turnover at the facility level, which increases employers' recruitment and training costs (Becker, 1962; Hashimoto, 1981). Previous empirical studies consistently estimate high costs of turnover at nursing homes (Li and Jones, 2013). For example, using data from cost reports and instrumenting for turnover using geographic variation in outside employment options, Mukamel et al. (2009) finds that a 10% increase in nursing home staff turnover was associated with a 2.9% increase in costs.

In order to investigate the relationship between minimum wages and the allocation of hours across workers of different levels of experience, we compare the effects of minimum wage increases on weekly hours for new hires and tenured workers. In these analyses, new hires (which we also refer to as "non-tenured employees") are those who were hired during the fiscal year. "Tenured" workers are those who were already employed before the start of the fiscal year. We further divide tenured workers into terciles of tenure at the national level based on their number of hours worked at the facility before the start of the fiscal year.[14]

There are substantial differences in firm-specific experience across these experience terciles (see Table 2). In fiscal year 2019, workers in the first (lowest) tercile of tenure had less than 761 hours of firm-specific experience (about 4.5 months of full-time work), while those in the 3rd (highest) tercile had at least 2,616 hours of experience (approximately 15 months of full-time work). These differences in firm-specific experience are important when considering the nature of CNA work, which requires limited formal training and has a substantial on-the-job learning component.

In the context of minimum wages, changes in employment across different tenure levels raise distributional considerations, given that wages generally increase with experience (Mincer, 1991). Table 1 indicates that this relationship holds among CNAs using wage data from annual facility cost reports submitted to CMS, with the most experienced workers receiving 10.9 percent more than new hires. (See Appendix A.2 for details.) That more experienced workers earn more than new hires implies that the "bite" of the minimum wage is strongest for newly-hired workers, while their more experienced colleagues receive only muted wage increase through spillover effects. Accordingly, higher minimum wages reduce wage inequality in the bottom of the earnings distribution (Autor et al., 2016; Cengiz et al., 2019).

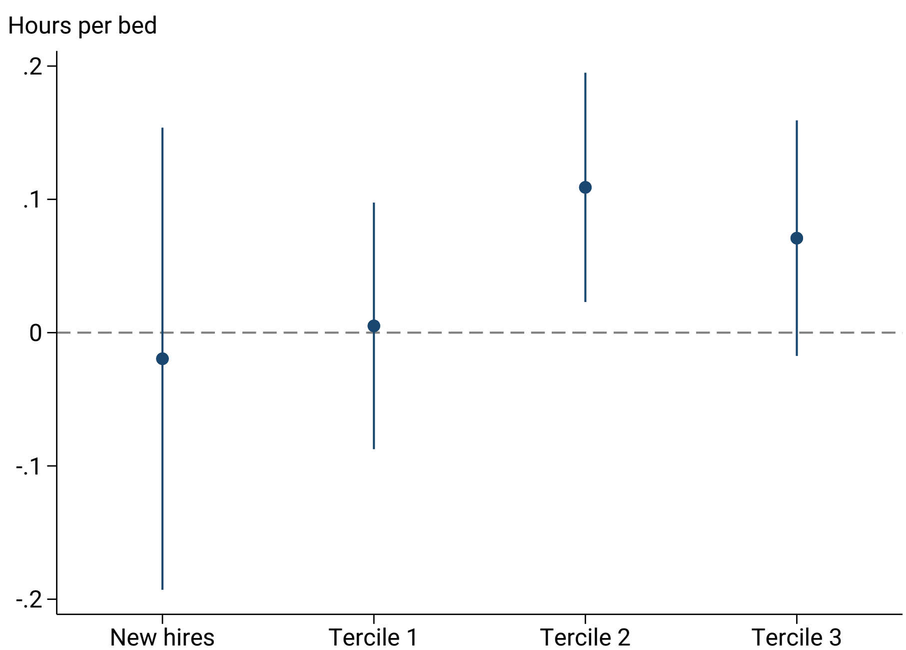
From the firm's perspective, this reduction in low-wage inequality implies that the *relative*

[14] Since we define worker tenure based on experience at the start of the fiscal year, tenure is not defined for the first year in our data (fiscal year 2017). Correspondingly, all analyses of worker tenure only consider outcomes for fiscal year 2018 and onward.

cost of allocating hours to newly-hired and low-tenure workers increases. Equivalently, the relative cost of allocating hours to the most experienced staff decreases. As we detail in Section 3.1, this compression incentivizes facilities to shift their use of labor towards more experienced staff.

Figure 5 shows the estimated effect of a minimum wage increase on the weekly hours of CNA labor employed per bed for each category of worker experience. These estimates are analogous to those in Table 3, but are disaggregated by tercile of tenure. We see that the allocation of labor to new hires and the least experienced workers does not significantly change, whereas facilities increase their total employment of workers in each of the top two terciles by approximately 6.5 additional minutes per bed-week when the minimum wage increases by 10 percent. In other words, the entire increase of 13 minutes per bed-week estimated in Table 3 is attributable to additional labor worked by employees in the top two terciles of firm-specific experience.

Figure 5: Hours Per Bed, CNAs by Tenure



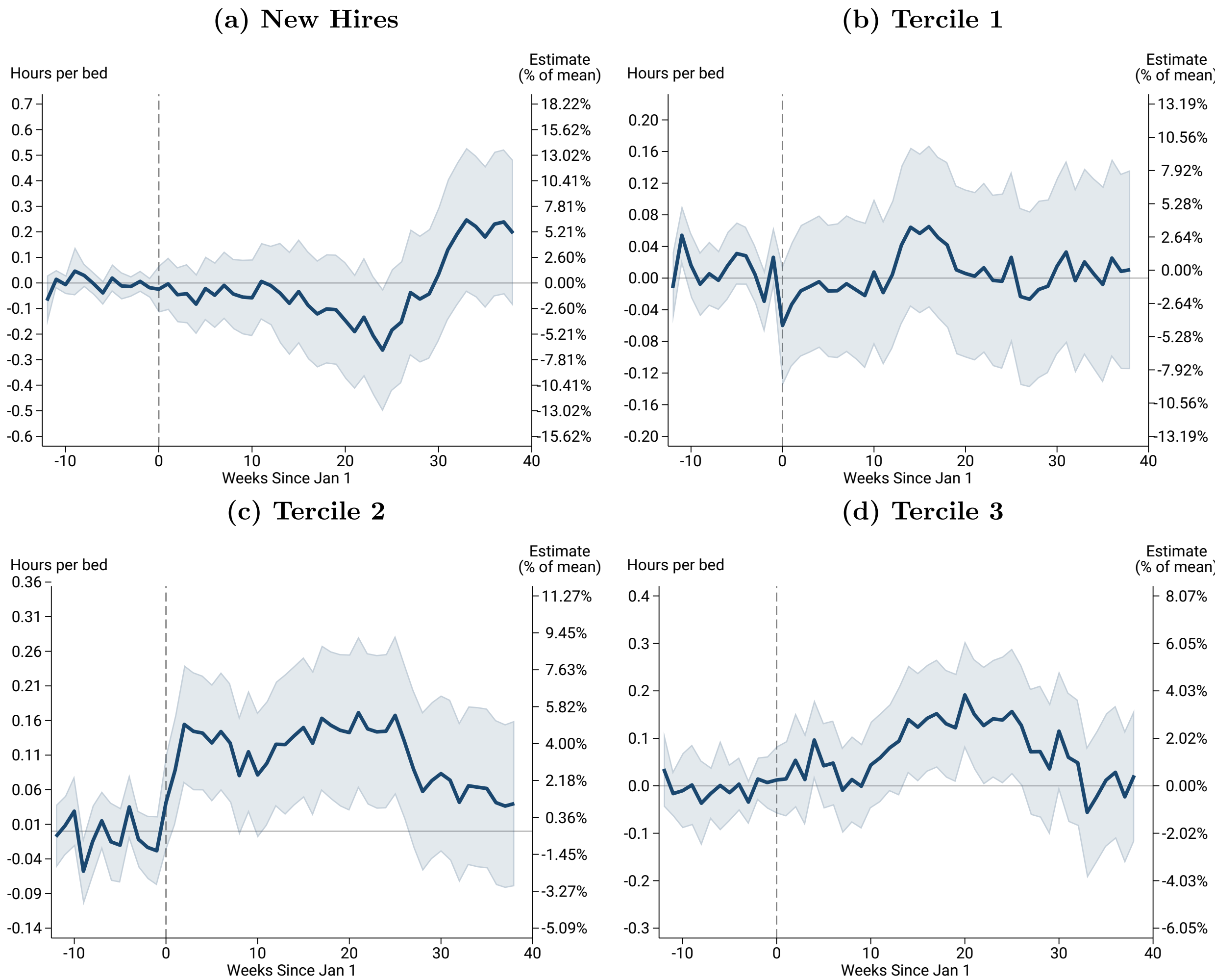
Notes. Figure shows weekly hours per bed for fiscal years 2018 through 2019 by new hires and workers employed at the start of the fiscal year. Tenure terciles are based on the national experience distribution for each fiscal year. Point estimates denote the θ_{DD} coefficient under the approach in Equation 3. Time unit is at the weekly level; treated unit is the facility-by- fiscal year. Vertical bars denote 95% confidence intervals with standard errors clustered by county.

The shift in the allocation of labor towards tenured workers in the nursing home sector is broadly consistent with existing empirical work that take a case study approach to local minimum wage changes. 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.

One unique feature of our data is that we can observe facilities' employment decisions at a very high frequency. While the previous literature has typically studied minimum wage changes at a relatively coarse quarterly or annual resolution, we are able to zoom in to examine the extent to which changes are immediate or accumulate throughout the fiscal year. In order to shed light on the reallocation dynamics at a granular weekly level, Figure 6 expands the aggregated θ_{DD} results in Figure 5 to an event study framework by plotting the weekly θ_{ES} coefficients from Equation 5.

Figure 6: 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 under the approach in Equation 5. Time unit is at the weekly level; treated unit is the facility-by-fiscal year. Shaded area denotes 95% confidence intervals with standard errors clustered by county.

Figure 6 shows nuanced patterns in the dynamics of the effect over the fiscal year. First, for each tenure group, we do not observe any differential patterns between treatment and control facilities in the weeks leading up to a wage increase, bolstering the plausibility of the parallel trends identifying assumption. Second, we do observe some immediate response in the weeks after the minimum wage increase. This is especially true for the second tercile, which experiences the full effect almost immediately.

Notably, while the magnitudes of the increases are similar for the second and third tercile, the increase for the third tercile is less immediate than the increase for the second tercile. This may reflect that firms are less able to immediately adjust the allocation of labor to their most experienced workers. One reason for this is that the majority of the most experienced workers are already working full-time, and more than a third already work overtime hours (Table 2). In contrast, about 70 percent of incumbent workers with firm-specific experience in the second tercile are working less than an average of 35 hours a week (Figure 4d). Correspondingly, we shall find in Sections 4.3.1 and 4.3.2, that an outsize part of the increase in allocation for the most experienced workers comes from increased retention rather than in increase in hours along the intensive margin, and this retention effect takes time to accumulate.

Finally, panels a and b of Figure 6 indicates no change in hours worked for new hires or the least experienced workers (tercile 1) for 6 months after a minimum wage increase, but that hiring rebounds towards the end of the period. The timing patterns we observe also suggest that indicate that quarterly aggregates may miss short-term responses: The timing of the increase for new hires is consistent with a setting where recruiting and hiring take time, and the first months of work are part-time or training roles before the employees take on more hours.

4.3 Disaggregating the Retention and Hours Effects

In Section 4.2, we estimate that firms adjust their total labor employment towards more tenured workers in response to minimum wage increases. In this section, we aim to disaggregate the extent to which responses occur along the extensive margin (the "retention effect") and the intensive margin (the "hours effect").

Whereas the previous section focused on the total employment levels of different types of workers at the *firm* level, this section examines effects on retention and hours at the *worker* level. There is substantial variation in the composition of staff tenure across firms—some firms rely more on new hires and others on experienced workers—so the worker-level approach is particularly valuable in providing estimates that are most informative about the impact of minimum wage from the perspective of low-wage workers.

4.3.1 Changes in Worker Retention

The total stock of workers at any period t is the number of workers employed in the previous period $t-1$ plus any new hires and minus any separations. In other low-wage labor markets, increases in the minimum wage reduce worker flows by lowering the hiring and separation rates (Portugal and Cardoso, 2006; Dube et al., 2016). These previously-established patterns are broadly consistent with job ladder models in which higher minimum wages reduce the arrival rate of better paying jobs, but existing work largely describes aggregate patterns without distinguishing across workers with varying amounts of experience and correspondingly, different wages.

Table 4: Hires and Separations

	New Hires (% of payroll)	Separations (% of payroll)			
		All	Tercile 1	Tercile 2	Tercile 3
Minimum Wage	-6.725	-1.441	-0.478	-1.183	-1.622
	(1.175)	(0.400)	(0.570)	(0.525)	(0.525)
Mean	73.34	34.64	49.51	35.76	21.14
Std. Dev.	41.86	15.20	19.75	18.26	17.93
Implied Representative Elasticity	-2.782	-0.902	-0.187	-0.745	-2.594
County Clusters	305	305	305	303	297
Facilities	1,469	1,468	1,464	1,452	1,389
Facility-Weeks	75,971	75,919	75,711	75,133	71,997

Notes. Table shows weekly hiring or separation rate for fiscal years 2018 through 2019 under the approach in Equation 4. Time unit is at the weekly level; treated unit is the facility-by-fiscal year. 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, $t-1$. Observations with no separations are excluded from the analyses. Standard errors clustered by county in parentheses. "Implied representative elasticity" calculated as the percent change in hires/separations evaluated at the end-of-year mean divided by the percent change in the minimum wage among facilites experiencing a minimum wage change.

Table 4 shows the estimated effects of how minimum wages change the weekly hiring and separation rates, measured as the number of new hires or the number of separating workers divided by the total number of workers in each category at the start of the fiscal year. Similar to the existing literature, we find a reduction in turnover, measured by both the hiring rate and the overall separation rate. On average, 35 percent of CNAs will leave their firm within the year; a minimum wage increase of at least 50 cents reduces this number by 1.4 percentage points for an implied elasticity of -0.9.

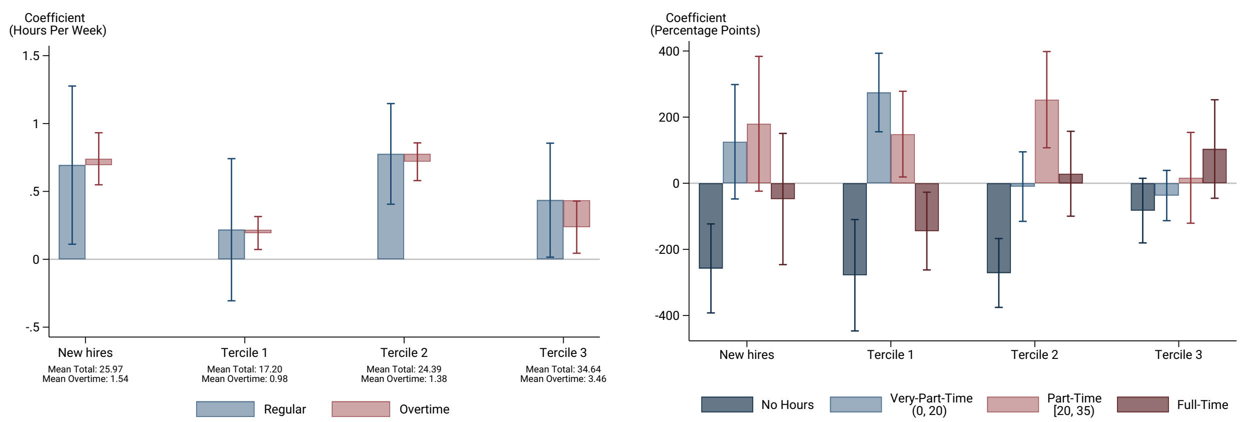
The remaining columns of Table 4 provide some of the first evidence on whether higher minimum wages affects retention of more or less experienced workers to different extents. Indeed, the average effect masks substantial heterogeneity across workers with different levels of firm-specific experience. When the minimum wage increases, it is the most experienced workers (those in the third experience tercile) that increase their retention rates the most, even as these workers already had the lowest separation rates.

4.3.2 Changes in Hours Allocated to Individual Workers

In addition to increasing retention of highly experienced workers and lowering retention of new hires, minimum wages may also affect the hours and shifts allocated to individual CNAs. Figure 4 shows 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. The variance in weekly shifts suggests that changes in the minimum wage could change the weekly hours for each individual worker.

Figure 7: Characteristics of Low-Wage Work

(a) Hours Per Worker **(b) Part-Time and Full-Time**



Notes. Figure shows the change in weekly hours (panel a) or the likelihood of working part- or full-time (b) 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 estimated with the approach in Equation 3. Time unit is at the weekly level; treated unit is the facility-by- fiscal year. Vertical bars show 95% confidence intervals with standard errors clustered by county.

Changes in regular and overtime hours Figure 7 panel a shows that new hires and the most experienced workers work more regular-time hours (i.e., hours up to 40 per week) and the most experienced workers work fewer overtime hours after the minimum wage increase.[15] The overall change in hours per week is not significantly different across the experience distribution;

[15]We define the number of overtime hours based on state-specific legislation. Most states follow the federal requirements of overtime pay in excess of 40 hours a week; however, others have state regulations that are more binding. For example, California requires overtime pay for hours in excess of 8 hours a day (as well as the weekly 40 hour limit).

however, as baseline weekly hours are increasing in experience, there are no systematic patterns in the percentage change across the experience terciles.

Changes in part-time and full-time work Panel B considers other points of the hours distribution and indicates that a higher minimum wage increases the likelihood that workers across experience categories are more likely to work at least some hours in a given week. The margin of adjustment differs across the experience terciles: new hires and workers with relatively low levels of experience become more likely to work part-time (fewer than 35 hours a week), whereas the most experienced workers are increasingly working full-time.

Altogether, the patterns in Figure 7 are broadly 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 and Gopalan et al. (2021) find minimum wage increases did not decrease hours of incumbent workers. In the national nursing home industry, minimum wages also increase hours among incumbent workers, and we find a reduction in the likelihood new workers are hired, although conditional on being hired, hours worked among new workers increases.

4.3.3 Quantifying the Retention and Hourly Responses

Figure 8 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 effect and hours per worker effect to the overall allocation of hours for workers in each experience tercile. All regressions are weighted by the number of workers in order to provide a measure of employment from the perspective of workers.

The top panel shows changes in the hours per worker that combines retention and hours effect. This measure aggregates all hours worked by workers in each experience category in a given week, divided by the number of workers who were employed at the beginning of the fiscal year. We see no significant change among workers in the first experience tercile, whereas the second and third terciles experience an increase in hours worked over the first 1-2 months after the minimum wage increase that persists through the end of the 9-month period.

The center panel isolates the retention effect, measured as the number of workers who will work at least one shift in the future divided by the number of workers employed at the beginning of the fiscal year. The second and third experience categories experience an increase in retention that is similar in percentage terms. The least experienced workers experience a small, one-time increase in retention that is concentrated in the first month after the minimum wage hike and has fully faded out by the end of the 9-month period. For the most experienced workers, the retention effect grows over time at a fairly steady rate: 9 months after the minimum wage increase, these workers are about 2.5 percent more likely to be with their original employer.

Finally, the bottom panel isolates the hours per worker effect by measuring the total number of hours worked among current employees (e.g.: the denominator is the number of workers currently employed). Among the least experienced retained workers, hours begin to rise about 6 months after the higher wage becomes effective and continue to trend up over the following 3 months. The second tercile experiences a more immediate increase in hours worked that persists over the 9-month period.

For the more experienced workers in terciles 3, the increase in the number of hours is driven by greater retention. The most experienced workers are not working significantly more hours 9 months after the minimum wage than they were before (panel i); however, due to fewer separations, there are more of these workers available (panel f). More precisely, three months after the wage increase, the retention and individual worker effects 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 for the second tercile and all of the gains for the third.

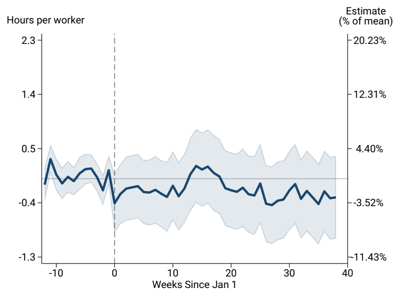
4.4 Simulating the Long-Run Impact of Increasing the Minimum Wage

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.

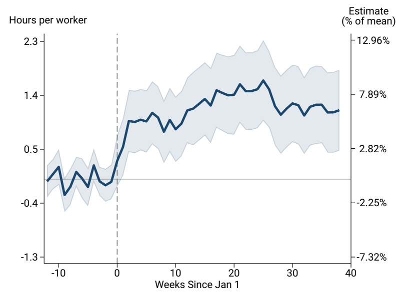
In this section, we simulate these potential *long-run* impacts of minimum wage increases. There are two primary channels through which we expect effects to accumulate over the long-run. The first is that the estimated change in hiring rates, retention rates, and hours allocations for each tenure tercile 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

Figure 8: Changes in Hours per Worker, With and Without Changes in Retention

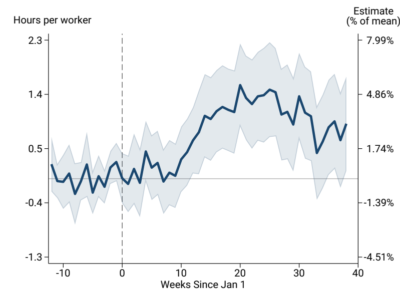
(a) T1, Combined



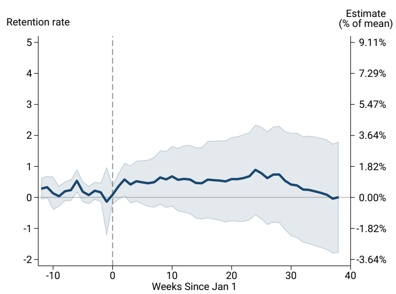
(b) T2, Combined



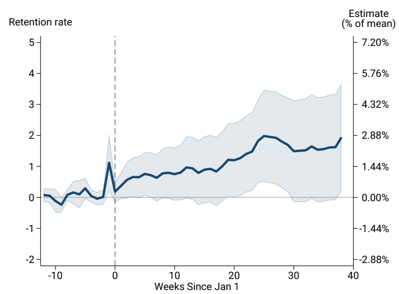
(c) T3, Combined



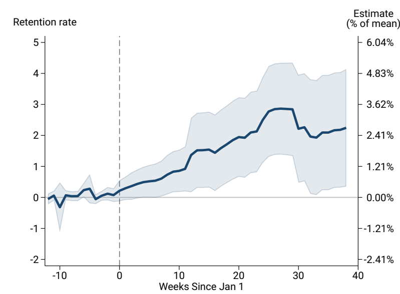
(d) T1, Retention



(e) T2, Retention



(f) T3, Retention



(g) T1, Hours-per-worker

(h) T2, Hours-per-worker

(i) T3, Hours-per-worker

Notes. Figure shows the change in weekly hours per worker by experience tercile for fiscal years 2018 and 2019, estimated under the approach in Equation 5. Time unit is at the weekly level; treated unit is the facility-by- fiscal year. Panels a, d, and g 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, e, and h report coefficients where the outcome variable is whether the employee is still employed at the facility. Panels c, f, and i isolate the hours 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.

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 **??**.

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.[16]

Next, we simulate hiring rates under the assumption that facilities maintain the levels of patient care (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 B1. 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.[17] 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 8). 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

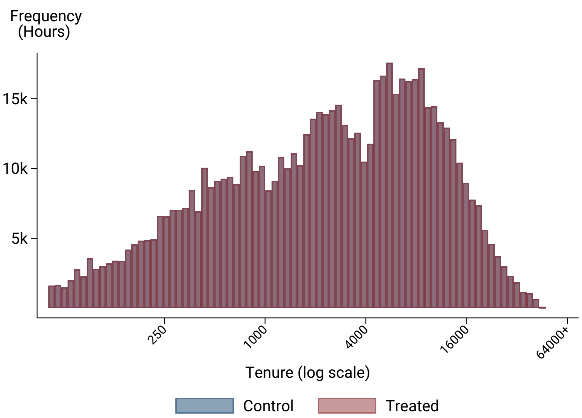
[16] Appendix A.7 describes the process for calculating retention rates of new hires.

[17] 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.

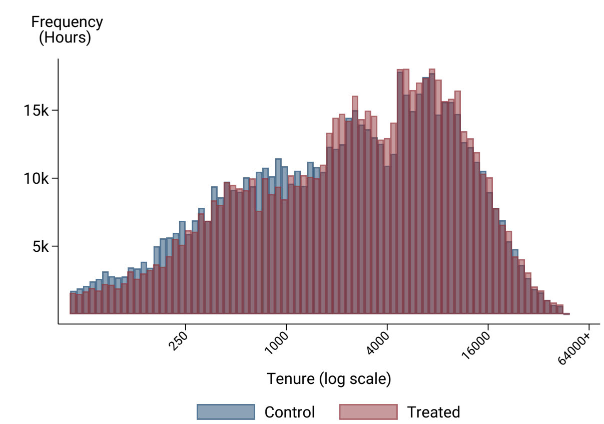
the employee composition reaches an equilibrium (up to seasonal variation).[18] From this initial equilibrium, we compare the simulation progresses with and without a $1 increase in the minimum wage. We run these simulations week-by-week until the employment composition under the $1 increase in the minimum wage reaches a new equilibrium.

Figure 9: 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

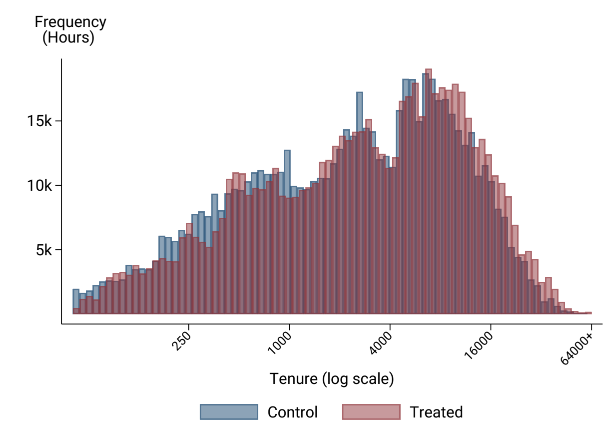


Figure 9 presents the simulated impact of increasing the minimum wage by $1. Panel 9a shows the initial equilibrium hours-weighted tenure distribution at the start of the fiscal year during which the $1 increase will be implemented. This represents the tenure composition of employee hours—or equivalently, the tenure composition of care that residents receive—prior to the minimum wage

[18] 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.

increase. Panel 9b 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 255 and 336 tenure hours, respectively.

Panel 9c 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 897 (18%) and 484 (18%) 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 4 percentage points from the baseline of 56%. 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 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 shift the allocation of hours to the most experienced workers. Higher minimum wages increase the retention rate among the most experienced workers, while reducing the number of new hires. In the short-term, the most experienced workers also work more hours, but over time, the retention effect becomes increasingly important. Nine months after the minimum wage increases, increases in retention can account for all of the reallocation of hours . 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 (Abelson, 2021; Gandhi et al., 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, 2022). 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.

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.

Acemoglu, Daron, "Good jobs versus bad jobs," *Journal of labor Economics*, 2001, *19* (1), 1–21.

Antill, Samuel, Jessica Bai, Ashvin Gandhi, and Adrienne Sabety, "Healthcare Provider Bankruptcies," *Unpublished Manuscript*, 2022.

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.

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.

Callaway, Brantly and Pedro HC Sant'Anna, "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

__ , Andrew Goodman-Bacon, and Pedro HC Sant'Anna, "Difference-in-differences with a continuous treatment," *arXiv preprint arXiv:2107.02637*, 2021.

Castle, Nicholas G and John Engberg, "Staff turnover and quality of care in nursing homes," *Medical care*, 2005, pp. 616–626.

— , — , **and Aiju Men**, "Nursing home staff turnover: Impact on nursing home compare quality measures," *The Gerontologist*, 2007, *47* (5), 650–661.

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, Lisa B Kahn, and Jonathan Meer, "Dropouts need not apply? The minimum wage and skill upgrading," *Journal of Labor Economics*, 2021, *39* (S1), S107–S149.

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.

Flinn, Christopher J, "Minimum wage effects on labor market outcomes under search, matching, and endogenous contact rates," *Econometrica*, 2006, *74* (4), 1013–1062.

Friedrich, Benjamin U and Martin B Hackmann, "The Returns to Nursing: Evidence from a Parental-Leave Program," *The Review of Economic Studies*, 01 2021, *88* (5), 2308–2343.

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.

Goldsmith, Arthur H and Jonathan R Veum, "Wages and the composition of experience," *Southern Economic Journal*, 2002, *69* (2), 429–443.

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.

Li, YIN and Cheryl B Jones, "A literature review of nursing turnover costs," *Journal of nursing management*, 2013, *21* (3), 405–418.

Loomer, Lacey, David C. Grabowski, Huizi Yu, and Ashvin Gandhi, "Association between nursing home staff turnover and infection control citations," *Health Services Research*, 2022, *57* (2), 322–332.

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.

Ruffini, Krista, "Worker earnings, service quality, and firm profitability: Evidence from nursing homes and minimum wage reforms," Technical Report, Review of Economics and Statistics 2022.

Sacarny, Adam, "CMS Hospital Cost Report (HCRIS) Data 2000-2017," https://github.com/asacarny/hospital-cost-reports 2018.

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

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.

Small, Kenneth A, Erik T Verhoef, and Robin Lindsey, *The economics of urban transportation*, Routledge, 2007.

A Appendix

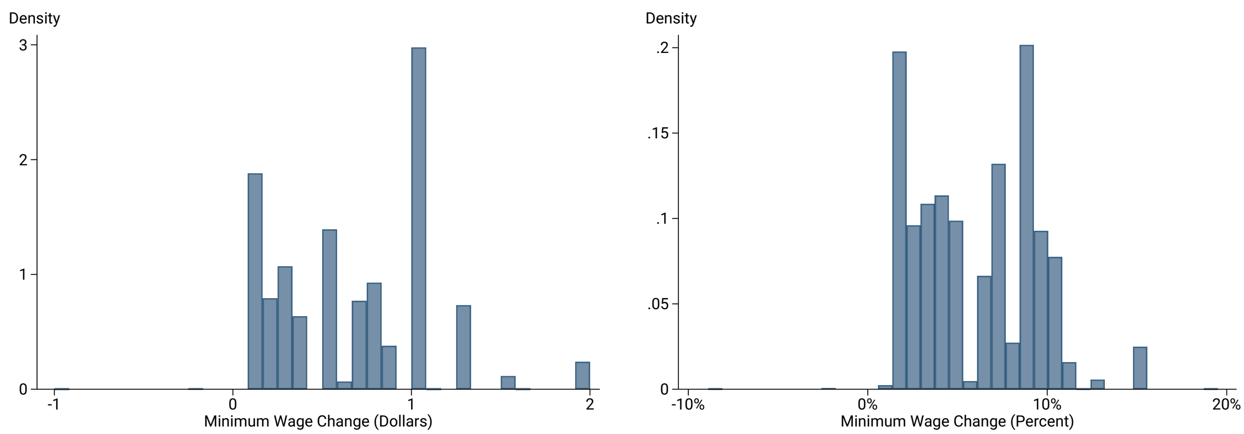
A.1 Minimum Wage Statistics

Appendix Table A1: 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	8.88	9.56	10.39
Median Minimum Wage	8.25	9.25	10.20
Share of Facilities Experienced A Minimum Wage Change	0.61	0.66	0.80
Share of Facilities Experienced A Minimum Wage Change (At Least $0.50)	0.34	0.36	0.56
Average Size of Minimum Wage Changes (At Least $0.50)	0.95	0.88	0.92

Appendix Figure A1: Size of Minimum Wage Changes

(a) Dollars **(b) Percent**



A.2 Experience Wage Premium

For each facility's annual cost reporting period in fiscal years 2018 and 2019, we calculate the total share of hours worked by new hires and workers in each of the tenure terciles j. The cost report data only includes the total amount paid in wages to each occupation and does not provide worker-level information. However, note that total wage expenditures on CNA workers is the number of hours worked by workers in each experience category multiplied by the average hourly wage among those workers. This identity allows us to use the reported CNA wage from the cost reports to estimate regressions of the form:

$$log(CNAwage)_{it} = \sum_{j=0}^{3} \beta_j log(\%hours_{jit}) + \gamma_t + \varepsilon_{it} \tag{6}$$

Table 1 indicates that on average, wages are increasing in experience and CNAs in the third experience tercile earn about 10.9 percent more than new hires. This relationship is not sensitive to the inclusion of controls for time-varying facility characteristics.

A.3 PBJ data construction

The raw micro PBJ data include a facility-specific identifier for each employee, the daily date each shift occurred, the number of hours worked that shift (up to 2 decimal places), the occupation associated with that shift (e.g.: CNA, CNA in training, RN, director of nursing), and whether the worker was compensated with an hourly wage, annual salary, or payment through a contract agency for those hours.

We aggregate the individual-level data to the facility-by-week level for each occupation and pay type in Table 3 and Figure 5. The remaining results aggregate to the occupation-experience-pay level for each facility-week. We exclude the first and last four weeks that a facility appears in the data over the October 2016 through December 2019 period, as the initial and last weeks may represent a facility opening (and scaling up production) or closing (and scaling down production). By a similar rationale, we drop facilities that have a hire or separation rate of 100 percent in any single week. In order to obtain a "per-bed" measure of each outcome (Sections 4.1 and 4.2, we divide the number of hours and the number of workers by the number of certified beds in a fiscal year, as reported through LTCFocus. In order to obtain a "per worker" measure, we divide the outcome by the number of workers on payroll (results without the retention effect) or the number of workers on payroll at the start of the fiscal year plus any new hires (results that include the retention effect).

We define experience terciles based on the national distribution of hours worked at the start of fiscal years 2018 and 2019. For example, when determining an individual's experience tercile for fiscal year 2018, we first calculate the number of facility-specific hours worked since the beginning of our data (October 2016) for workers that were employed as of October 1, 2018. The first tercile of workers had worked between 0 and the 33rd percentile; the second tercile between the 33rd and 67th percentile; and the third tercile had worked above the 67th percentile. We repeat the exercise for fiscal year 2019. All workers who were hired after October 1 are in the "new hires" category.

We do not include fiscal year 2017 in the experience analyses as the PBJ data is left-censored at October 1, 2016 and we are unable to calculate employee histories prior to this date.

A.4 Defining Nursing Home Labor Market Concentration

This section describes how we construct a facility-specific measure of nursing home labor market concentration that we use to restrict our analysis to facilities facing substantial labor market competition. In brief, the measure is constructed in two steps. First, for potential nursing home workers in each Census block, we measure the concentration of potential nursing home employers by constructing a Herfindahl–Hirschman index (HHI) of nursing homes within typical commute time of the block. Second, we measure the level of labor market competition faced by each facility as the weighted average HHI of the Census blocks within a typical commute time of the facility.

A.4.1 Geographical boundaries of local labor markets

In order to calculate labor market concentration, we first define the geographical boundary of a local labor market, approximated by using the distance that a worker is likely willing to commute to a potential employer. The Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) data contains commute flow dynamics between census blocks, as well as employee workplace and resident characteristics, summarized in Table A2, which enables us to locate potential workers.

Appendix Table A2: LODES Data File Descriptions

File Type	Includes	Uses
Origin-Destination (OD)	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 (WAC)	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 (RAC)	Residence block and the number of jobs in the Health Care and Social Assistance sector	Used to weight block-level HHI.

We start with the LODES Origin-Destination (OD) data to calculate the employment distribution of each workplace block over the residential census blocks to obtain the commuting distance distribution and commute time of all potential workers. Potential workers are defined as the number service sector jobs outside of the trade, transportation, and utilities industries, (the narrowest service sector categorization available in the LODES data).

Second, 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.

Third, we match the workplace blocks for healthcare and social assistance jobs from the Workplace Area Characteristics (WAC) data to the nursing home coordinates. In order to overcome possible mismatches due to the lack of precision in the data, we compare the block level workforce distribution in the WAC data to the number of workers at the facility from the Payroll Based Journal (PBJ) data used in the analysis using the following algoritm:

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.[19] 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.

[19] 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.

A.4.2 Calculating HHI

Identifying each worker's potential employers: After identifying the location of each facility and the commuting distribution, we identify all of the facilities that constitute a potential worker's employment choice set conditional on the worker's residential Census block. In order to obtain a realistic representation of how far a worker may be willing to commute, we implement the Bing Maps Distance Matrix API to measure the driving distance and travel time between residence and potential workplaces.[20] This measure more accurately reflects commuting patterns than the simple geodesic distance.

For each commuting zone (CZ) in which facilities are located, demarcated by the Bureau of Economic Analysis shapefiles, we set the maximum threshold for commute time as the 75th percentile of commute flows.[21] We then identify the employee's choice set of potential employers as all of the facilities within this commuting duration as shown in Figure 2a, from the worker's residence location(34 minutes for this part of LA) provided by the RAC data.[22] Then for each worker's residence 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.

Facility-level HHI: In order to obtain a measure of labor market concentration faced by the *facility*, aggregate each worker's residential HHI to the facility level:

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

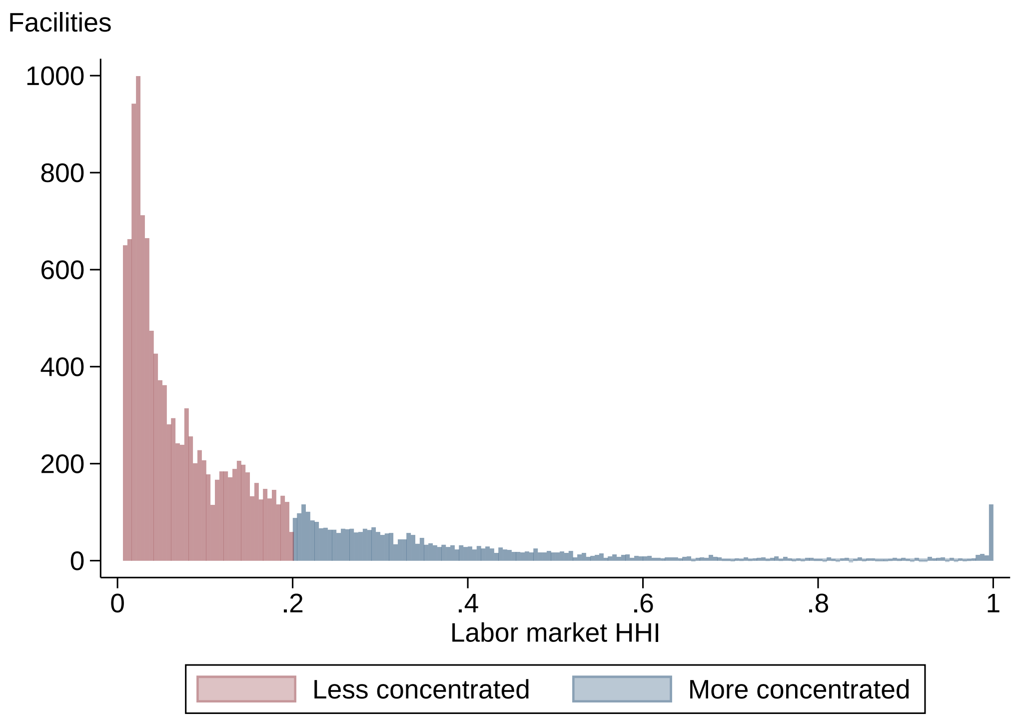
[20] To ensure consistency, the traffic data collected are from July 17 2019 at 8AM.

[21] Outliers are winsorized at one hour.

[22] 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.

where R_b is the number of potential workers living in block b. Figure A2 plots the facility-level HHI distribution, divided at 0.2 (approximately the 80th percentile). The distribution is highly skewed to the right: most facilities face relatively high competition in the local labor market, but some areas operate with a single provider. Our analytical sample focuses on facilities in the less concentrated markets.

Appendix Figure A2: Distribution of Labor Market HHI



A.5 Calculating lower-tail wage inequality

In order to calculate the experience premium, we use wages paid to CNAs from facility annual cost report data from HCRIS. We then merge the count of hours worked by CNAs in each tenure tercile during the reporting period and estimate equations of the form: $log(CNAwage_{it}) = \sum_{j=0}^{4} \beta_j \% hrs_{jt} + \gamma_t + \varepsilon_{it}$ for facility i and reporting period beginning in quarter t. The β_j coefficients on the share of hours worked by each experience level, j for new hires and each tenure tercile then yield the average return to experience for each experience category. Under this approach, we find that workers in the third tercile earn an average of 10.86 percent more than new hires.

A.6 Robustness: Two-way fixed effects

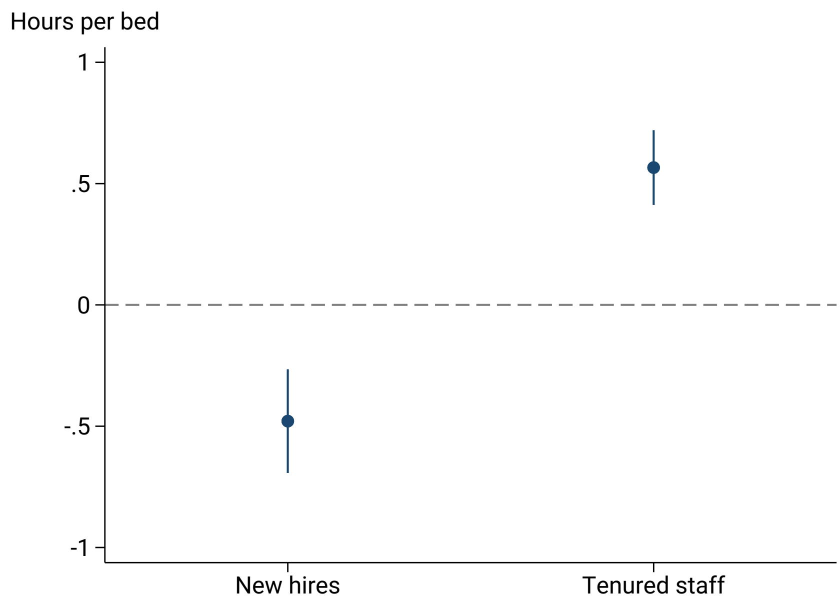
Appendix Table A3: Hours and Number of Employees per Bed, by Occupation and Pay Type, TWFE

	CNA Positions			Other Nursing Staff		Occupancy Rate
	Wage	Contract	Salaried	LPN	RN	
Panel A: Weekly Hours per Bed						
Minimum Wage	0.094	-0.015	0.009	0.039	-0.028	0.001
	(0.050)	(0.013)	(0.008)	(0.021)	(0.016)	(0.001)
Mean	12.97	0.35	0.06	4.86	2.90	0.83
Std. Dev.	4.31	1.16	0.77	2.31	2.67	0.16
Implied Representative Elasticity	0.064	-0.374	1.338	0.070	-0.086	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	0.13	0.03	0.10	0.21	
Implied Representative Elasticity	0.027	-0.047	0.429	0.049	-0.018	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week	Yes	Yes	Yes	Yes	Yes	Yes
FE: Facility $\times$ FY	Yes	Yes	Yes	Yes	Yes	Yes
County Clusters	1,310	1,310	1,310	1,310	1,310	1,310
Facilities	8,878	8,878	8,878	8,878	8,878	8,878
Facility-Weeks	851,691	851,691	851,691	851,691	851,691	851,691

Appendix Table A4: Worker Flows - Hires/Separations Rates, TWFE

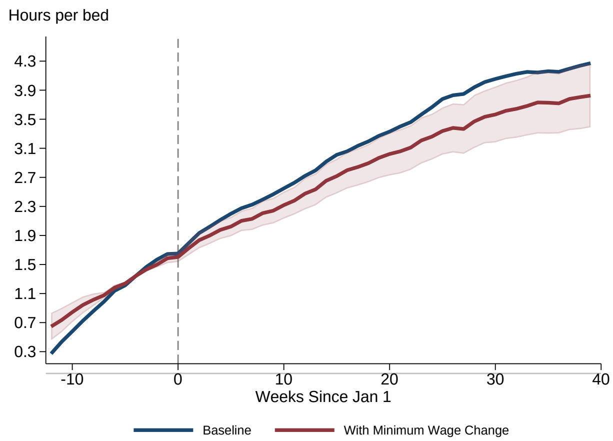
	New Hires (% of payroll)	Separations (% of payroll)				
		All	New Hires	Tercile 1	Tercile 2	Tercile 3
Minimum Wage	0.037	-0.049	0.390	-0.006	-0.091	-0.108
	(0.088)	(0.037)	(0.136)	(0.072)	(0.027)	(0.024)
Mean	1.64	1.63	4.30	1.64	1.00	0.54
Std. Dev.	7.98	3.34	11.09	5.92	4.38	3.81
Implied Representative Elasticity	0.224	-0.303	0.905	-0.035	-0.909	-2.020
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	521	521	521	521	521	514
Facilities	3,437	3,437	3,437	3,437	3,437	3,437
Facility-Weeks	298,249	298,249	298,249	298,249	298,249	298,249

Appendix Figure A3: Hours per Bed, CNAs by Tenure, TWFE

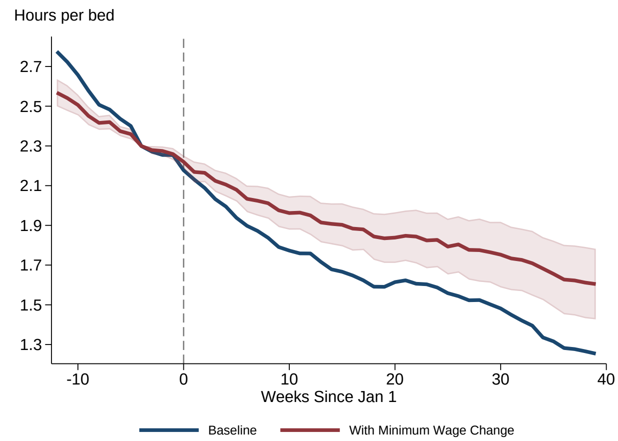


Appendix Figure A4: Dynamic Effects of Minimum Wages on Hours Worked, TWFE

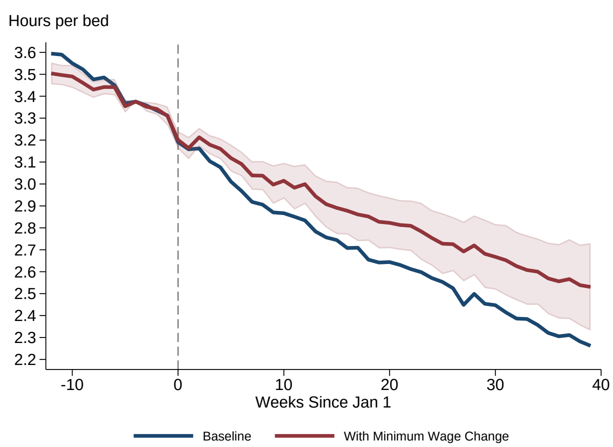
(a) New Hires



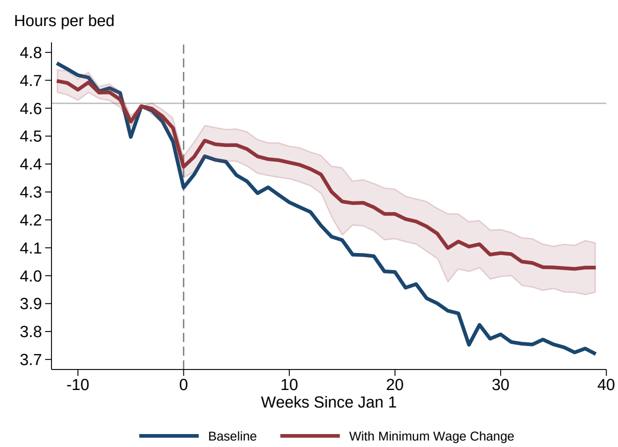
(b) 1st Tenure Tercile



(c) 2nd Tenure Tercile



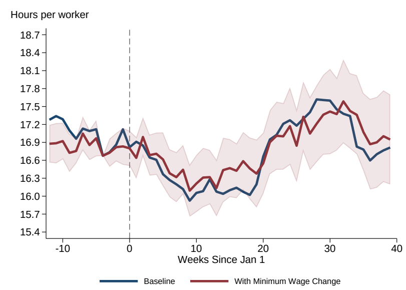
(d) 3rd Tenure Tercile



Appendix Figure A5: Changes in Hours per Worker, With and Without Changes in Retention, TWFE

(a) T1, Combined

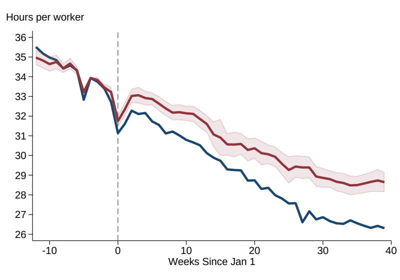
(b) T1, Hours-per-worker



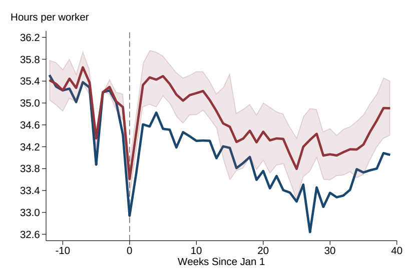
(c) T2, Combined

(d) T2, Hours-per-worker

(e) T3, Combined

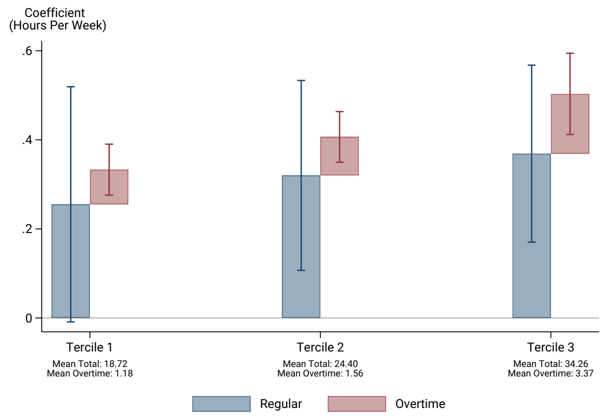


(f) T2, Hours-per-worker

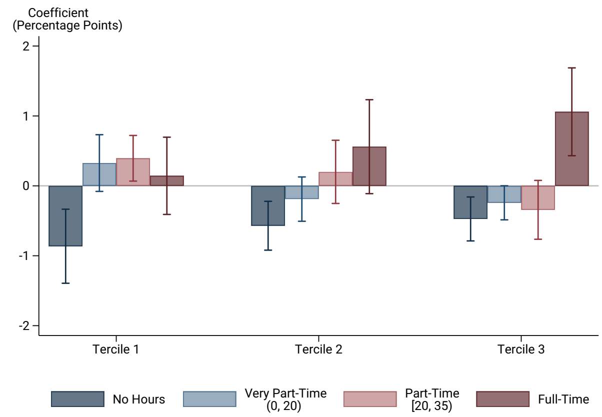


Appendix Figure A6: Characteristics of Low-Wage Work, TWFE

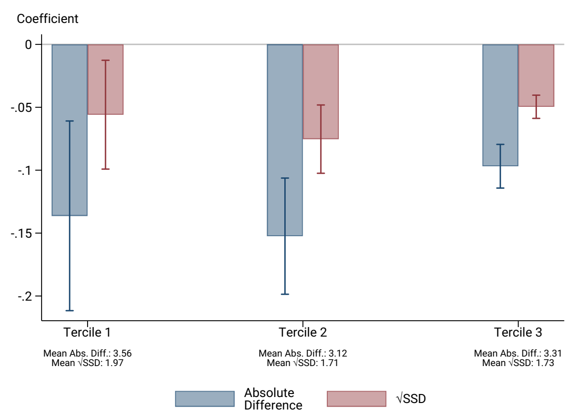
(a) Hours Per Worker



(b) Part-Time and Full-Time



(c) Scheduling Volatility



A.7 Estimates used in simulation

The simulation includes three steps: 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 a $1 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.[23]

On the first week of each fiscal year, we begin by (re-)assigning a retention curve to each worker based on the worker's tenure at the start of the fiscal year. Workers in the control group are assigned the empirical retention curve for workers in facilities without a minimum wage increase over the analysis period. Workers in the treatment group are assigned the retention curve corresponding to the event study analysis in Figure A7. 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. 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 B1 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 **??**. 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

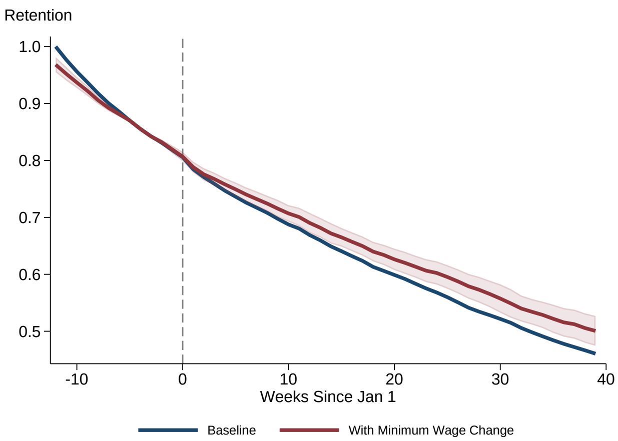
[23] In the first simulated year, the weekly estimates are applied directly. Starting from the second simulated year, we use the treatment effects averaged across the base week and the end of the fiscal year. This is equivalent to taking the difference in the average slopes of the curves in Figure A7.

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 A9 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 **??** are subsequently added.

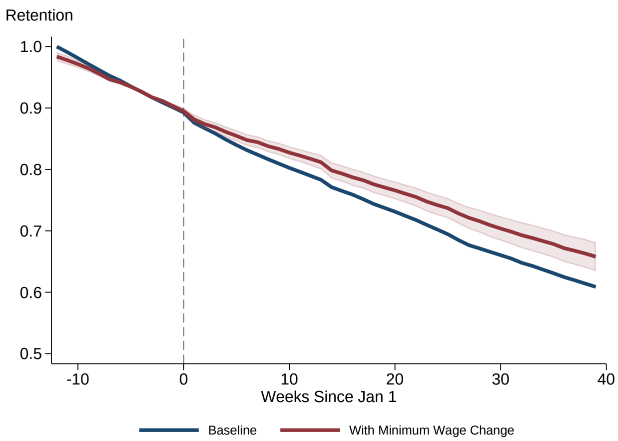
Long-run Equilibrium In order to illustrate the effect of minimum wage in the long run, we simulate pre-treatment using this procedure assuming only the base case scenario until the tenure distribution reaches an equilibrium. Once this equilibrium is reached, the tenure distribution for the base case 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 A7: Retention

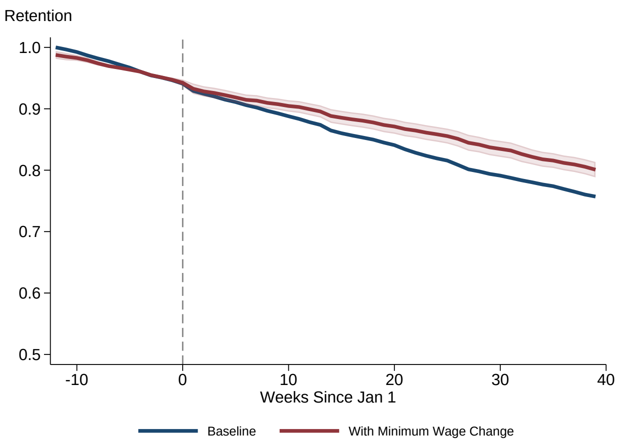
(a) 1st Tenure Tercile



(b) 2nd Tenure Tercile

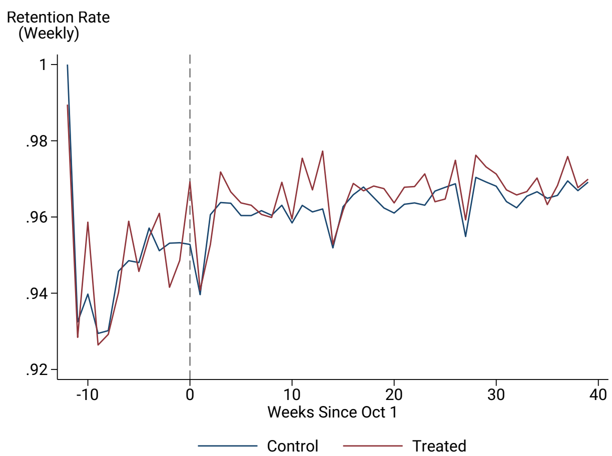


(c) 3rd Tenure Tercile

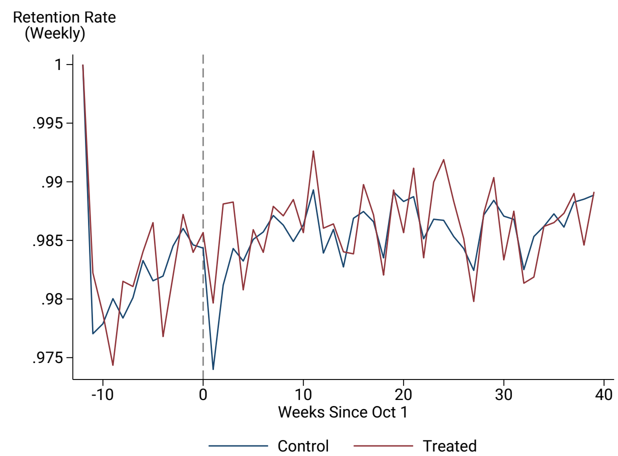


Appendix Figure A8: Weekly retention rate estimates

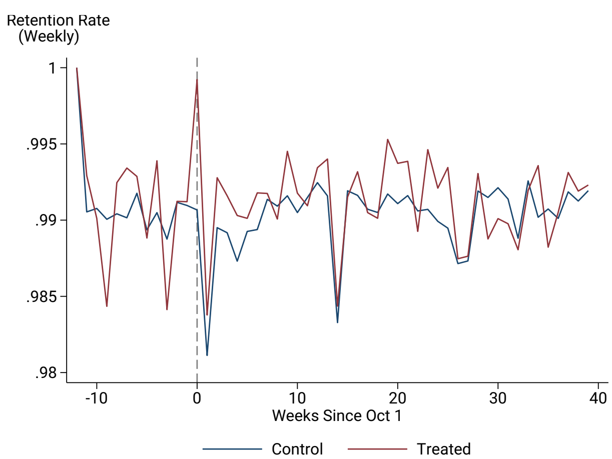
(a) New Hires



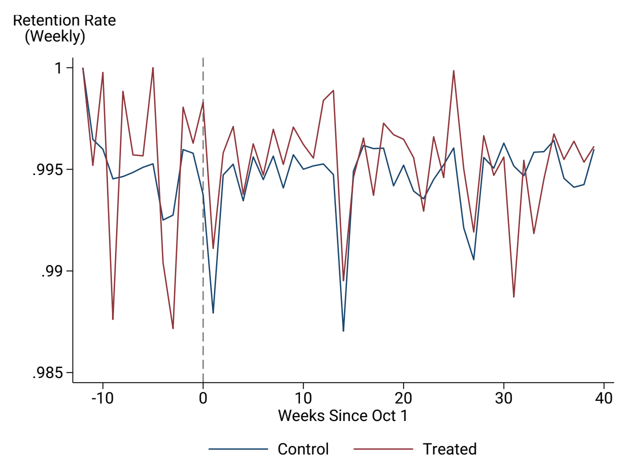
(b) Tercile 1



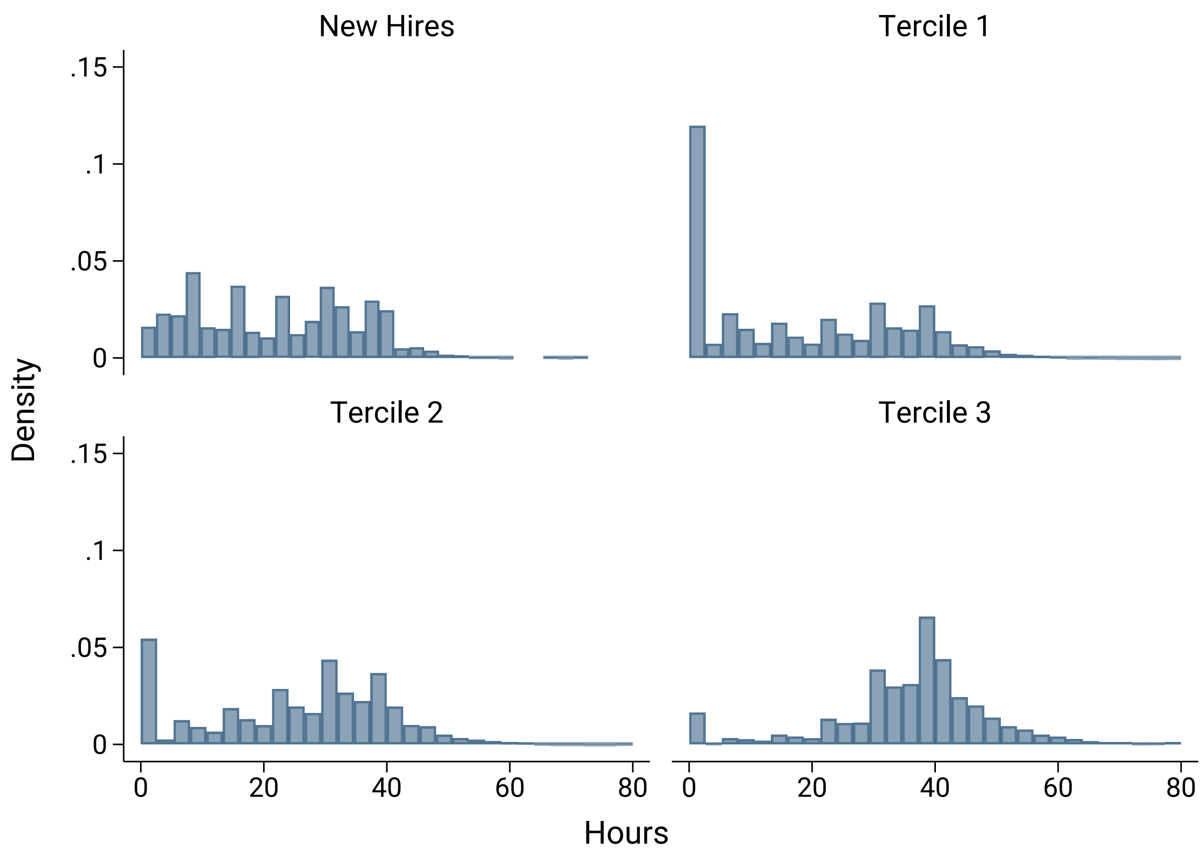
(c) Tercile 2



(d) Tercile 3



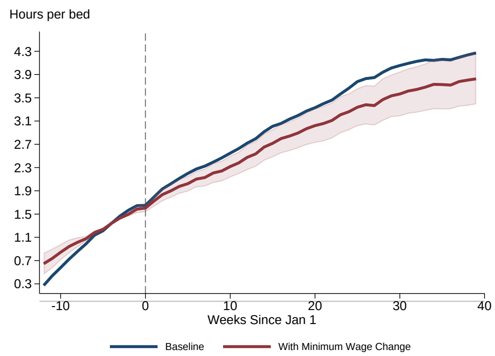
Appendix Figure A9: Empirical distribution on week 52



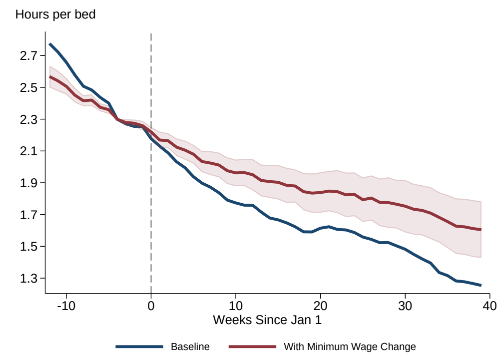
B Robustness: Two-way fixed effects

Appendix Figure B1: Dynamic Effects of Minimum Wages on Hours Worked, TWFE

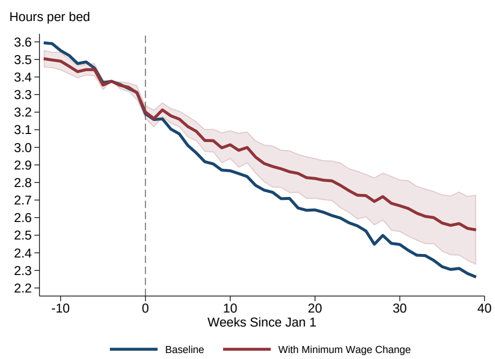
(a) New Hires



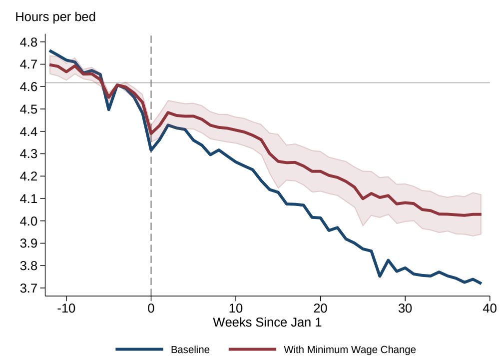
(b) Tercile 1



(c) Tercile 2



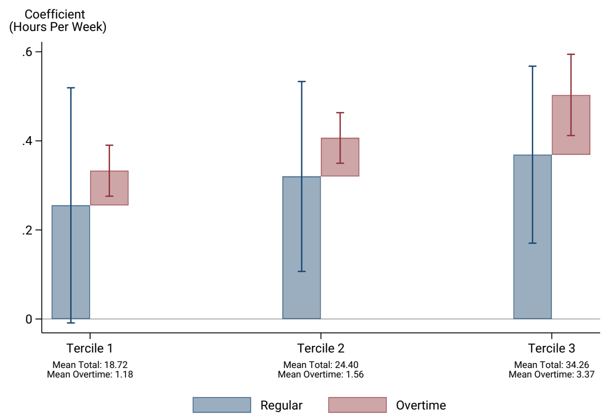
(d) Tercile 3



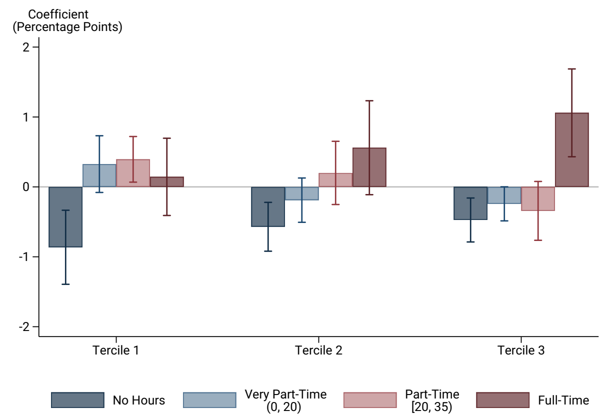
Notes. Figure shows the change in weekly hours worked among CNAs paid an hourly rate in fiscal years 2018 and 2019 by tenure tercile. Tenure terciles are based on the national experience distribution for each fiscal year. All specifications estimated with TWFE event studies. Blue solid line shows average patterns for facilities that did not experience a minimum wage change; red line adds the event study coefficients to the control group mean. Vertical bars show 95% confidence intervals with standard errors clustered by county.

Appendix Figure B2: Characteristics of Low-Wage Work, TWFE

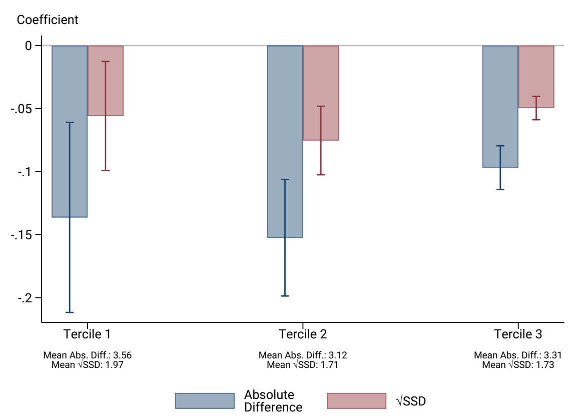
(a) Hours Per Worker



(b) Part-Time and Full-Time



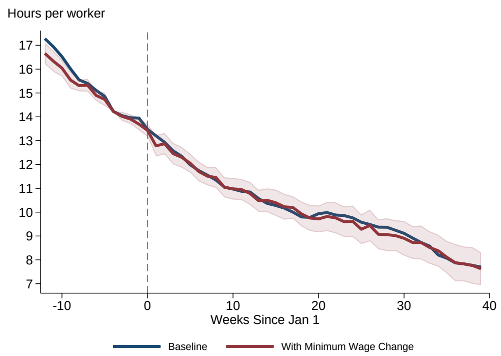
(c) Scheduling Volatility



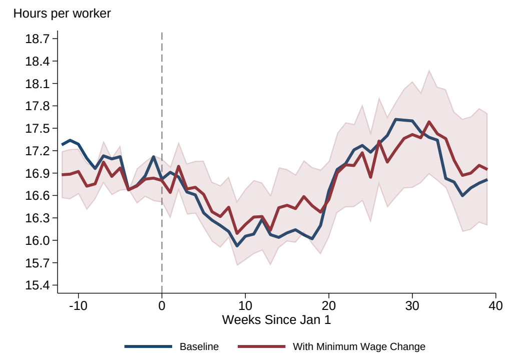
Notes. Figure shows the change in weekly hours (panel A), likelihood of working part- or full-time (B), and scheduling volatility (C) among CNAs paid an hourly rate in fiscal years 2018 and 2019. Tenure terciles are based on the national experience distribution for each fiscal year. All specifications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

Appendix Figure B3: Changes in Hours per Worker, With and Without Changes in Retention, TWFE

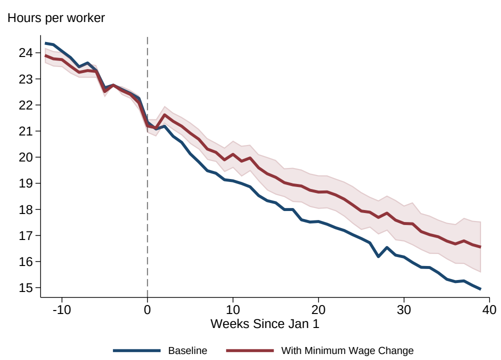
(a) T1, combined



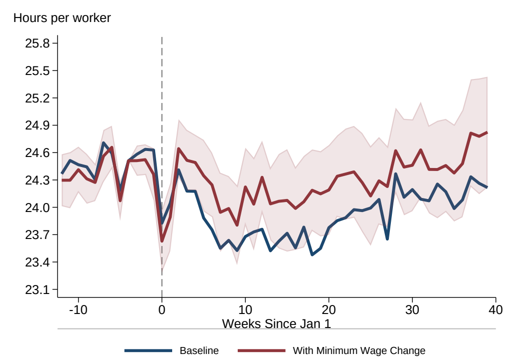
(b) T1, Hrs/worker



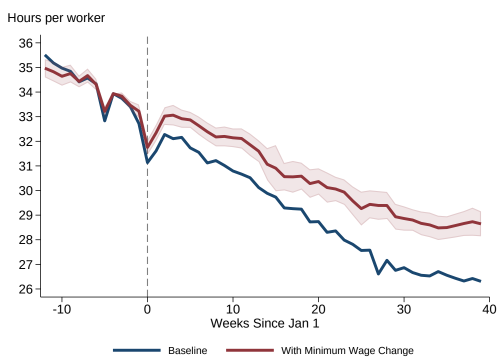
(c) T2, combined



(d) T2, Hrs/worker



(e) T3, combined



(f) T3, Hrs/worker

Notes. Figure shows the change in weekly hours worked among CNAs paid an hourly rate in fiscal years 2018 and 2019 by tenure tercile. Right panel includes hours for all workers employed at the start of the fiscal year; left panel only includes hours amongst those still employed by the firm in the current week. Tenure terciles are based on the national experience distribution for each fiscal year. All specifications estimated with TWFE event studies. Blue solid line shows average patterns for facilities that did not experience a minimum wage change; red line adds the event study coefficients to the control group mean. Vertical bars show 95% confidence intervals with standard errors clustered by county.

Appendix Table B1: Hours and Number of Employees per Bed, by Occupation and Pay Type, TWFE

	CNA Positions			Other Nursing Staff		Occupancy Rate
	Wage	Contract	Salaried	LPN	RN	
Panel A: Weekly Hours per Bed						
Minimum Wage	0.167	-0.023	0.014	0.069	-0.010	0.001
	(0.075)	(0.014)	(0.012)	(0.034)	(0.026)	(0.001)
Mean	13.14	0.33	0.07	4.79	2.90	0.83
Std. Dev.	4.22	1.07	0.90	2.45	2.64	0.15
Implied Representative Elasticity	0.127	-0.684	2.030	0.144	-0.033	0.016
Panel B: Weekly Number of Workers per Bed						
Minimum Wage	0.005	-0.000	0.000	0.002	0.001	
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	
Mean	0.51	0.04	0.00	0.18	0.13	
Std. Dev.	0.22	0.12	0.04	0.10	0.22	
Implied Representative Elasticity	0.096	-0.092	0.251	0.088	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	522	522	522	522	522	522
Facilities	3,437	3,437	3,437	3,437	3,437	3,437
Facility-Weeks	298,249	298,249	298,249	298,249	298,249	298,249

Notes. Table shows weekly hours per bed (panel A) and number of workers per bed (panel B) for fiscal years 2017 through 2019 under the TWFE approach. Standard errors clustered by county in parentheses.

Appendix Table B2: Worker Flows - Hires/Separations Rates, TWFE

	New Hires (% of payroll)	Separations (% of payroll)				
		All	Tercile 1	Tercile 2	Tercile 3	
Minimum Wage	0.037	-0.049	0.390	-0.006	-0.091	-0.108
	(0.088)	(0.037)	(0.136)	(0.072)	(0.027)	(0.024)
Mean	1.64	1.63	4.30	1.64	1.00	0.54
Std. Dev.	7.98	3.34	11.09	5.92	4.38	3.81
Implied Representative Elasticity	0.224	-0.303	0.905	-0.035	-0.909	-2.020
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	522	522	522	522	522	522
Facilities	3,437	3,437	3,437	3,437	3,437	3,437
Facility-Weeks	298,249	298,249	298,249	298,249	298,249	298,249

Notes. Table shows weekly hiring or separation rate for fiscal years 2018 through 2019 under the TWFE approach . 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, $t-1$. Standard errors clustered by county in parentheses.