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The Pay Gap Between Care Workers and Workers at Comparable Jobs

Matthew Dey, Mark Loewenstein, and David S. Piccone Jr.
U.S. Bureau of Labor Statistics

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Matthew Dey
Bureau of Labor Statistics

Mark A. Loewenstein
Bureau of Labor Statistics

David S. Piccone Jr.
Bureau of Labor Statistics

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Abstract

Home health and personal care aides play the important role of helping individuals with disabilities or chronic illnesses who need assistance with their daily living activities. This paper develops a methodology for estimating what workers in jobs requiring similar skills to home health and personal care aides are paid. The methodology that we develop can be applied to any occupation, but here we apply it to care workers. Our methodology draws heavily on the wage and employment information that is provided by the Bureau of Labor Statistics' Occupational Employment Wage Statistics program. A second key source of information is the Department of Labor's Occupational Information Network, which has information on a large number of job attributes. We also make use of the Current Population Survey, which has useful demographic information in addition to wages.

1 Introduction

Home health and personal care aides play the important role of helping individuals with disabilities or chronic illnesses who need assistance with their daily living activities. These workers, whom we will simply call care workers, will become increasingly important as the ranks of older individuals swell with baby boomers. As noted by Banerjee, Gould, and Sawo[2], care workers were among the hardest hit workers during the pandemic as a result of the high contact nature of their job.

Care workers' wages are quite low.[1] According to the Occupational Employment and Wage Statistics (OEWS) survey data, the median wage of care workers was $14.07 in 2021. The corresponding figure in the Current Population Survey (CPS) was $14.11.

Care workers are disproportionately composed of women, Hispanics, and immigrants and generally have a low level of education. In addition, as noted by Robertson, Sawo, and Cooper[5],

[1]Throughout this paper, we will use the terms "care workers" and "home health and personal care aides" interchangeably.

there are institutional factors that may affect their pay. Specifically, care workers are "paid by those they serve or their immediate family, private long-term care insurance, or through Medicare or Medicaid's Home and Community Based Services waiver program (HCBS) with the majority of workers being paid through the HCBS waiver program, which is administered at the state level through a federal waiver program."

In this paper, we develop a methodology for estimating what workers in jobs requiring similar skills to care workers are paid. The methodology that we develop can be applied to any occupation, but here we apply it to care workers. Our methodology draws heavily on the wage and employment information that is provided by the Bureau of Labor Statistics' Occupational Employment Wage Statistics (OEWS) program. A second key source of information is the Department of Labor's Occupational Information Network (O*NET), which has information on a large number of job attributes. Using these two data sets, we estimate how similar other occupations are to the care workers occupation. We then obtain a "comparable wage" estimate as a weighted average of the wages paid in similar occupations, where each occupation's weight depends on how similar it is to care workers. Our analysis also makes use of the Current Population Survey (CPS), which has useful demographic information in addition to wages.[2]

2 Comparable Wage Methodology

Let $\hat{w}_a^{COMP}$ denote the comparable log wage estimate for care workers in area a. We calculate the comparable wage as a weighted geometric average of the wages in other occupations in area a:

$$\hat{w}_a^{COMP} = \sum_o \pi_{o,a} ln(\bar{w}_{o,a}) \tag{1}$$

where $ln(\bar{w}_{o,a})$ denotes the log of the mean wage received by workers in occupation o and area a and $\pi_{o,a}$ is the weight attached to occupation o in area a. The weight for occupation o depends on how similar occupation o is to the care workers occupation, and how much employment there is in occupation o and area a.

We calculate the weights in several steps. Most of the work involves finding a way to use the O*NET information to weight various occupations according to their similarity with the care

[2]The OEWS no longer distinguishes between the extremely similar occupations home health and personal care aides, instead combining the detailed SOC codes 31-1121 and 31-1122. The CPS treats the home health and personal care aides as distinct occupations. When dealing with CPS data, we simply aggregate the detailed Census Occupation codes 3601 and 3602 into one that we call care workers.

workers occupation.

We choose variables in categories that represent basic job skill requirements (e.g., deductive reasoning, oral expression, trunk strength) and job attributes (e.g., frequency of decision making). All in all, we end up with 148 variables belonging to 11 distinct O*NET categories.

We also use the education level that is required for the job. This variable differs from the years of schooling variable found in demographic data sets, but one would expect the two variables to be positively correlated.

2.1 Factor Analysis

Many of the O*Net variables are highly correlated, reflecting the fact that they contain similar information. The first step in our analysis is to reduce the number of variables using factor analysis. We are able to boil down our initial list of 148 variables to 15 factors. These factors explain greater than ninety percent of the variation in the O*NET variables.

2.2 Distance Calculation

In order to calculate the comparable wage using equation (1), we need to obtain values for the weights $\pi_{o,a}$. We first normalize the factors to have mean 0 and variance 1 and then estimate the wage regression model:

$$ln(\bar{w}_o) = \beta_0 + \sum_{k=1}^{K} \beta_k F_{o,k} + \beta_{K+1} Y_o + \epsilon_o \tag{2}$$

where $ln(\bar{w}_o)$ is the log of the mean wage for occupation o, $F_{o,k}$ is the value of the k-th factor for occupation o, K is the total number of factors, Y_o is the normalized number of school years typically needed for occupation o (from O*NET), and ϵ_o is the error term. The factor coefficients, β_k, are used to estimate the distance D_o between occupation o and care workers using the Euclidean distance formula:

$$D_o = \frac{1}{K+1} \sum_{k=1}^{K} (c_k (F_{o,k} - F_{C,k})^2 + c_{K+1}(Y_o - Y_C)^2) \tag{3}$$

where $F_{C,k}$ is the value of the k-th factor for the care workers occupation and weight c_k are given by

$$c_k = \frac{|\beta_k|}{\sum_{k=1}^{K+1} |\beta_k|} \tag{4}$$

Note that we weight factors in terms of their importance in the wage function.

We consider two different specifications. In our first specification, we restrict the set of comparable equations to those that have the same education as care workers, in effect assigning a weight of 0 to occupations with different levels if education. In an alternative specification, we do not restrict the set of comparable equation to occupations with the same education. Instead, we include normalized education as an explanatory variable in the wage regression and modify the weights in (2) and the distance function (3) accordingly.

2.3 Constructing the Proximity Weights

The function $\hat{\theta}_o = exp(-exp(\alpha + \sigma D_o))$ is a natural function to use to weight the distance of occupation o from the care workers occupation. Not only does the proximity-related weight $\hat{\theta}_o$ vary inversely with the distance D_o, but this decline is faster than would occur with the single exponential $\hat{\theta}_o = exp(-(\alpha + \sigma D_o))$. We choose the parameters α and σ to solve the following two equations:

$$exp(-exp(\alpha + \sigma D_{min})) = \theta_{min} \tag{5}$$

$$exp(-exp(\alpha + \sigma D_{10\%})) = \theta_{10\%} \tag{6}$$

where $D_{10\%}$ is the distance from the care workers occupation to the occupation that is in the 10th percentile, when occupations are ranked in order of their distance from the care workers occupation. θ_{min} is the value $\hat{\theta}_o$ takes at the occupation o that is nearest to the care workers occupation and $\theta_{10\%}$ is the value that $\hat{\theta}_o$ takes at the occupation that is at the 10th percentile. We set $\theta_{min} = 0.99$ and $\theta_{10\%} = 0.01$.

The exact shape of the function depends on how many jobs have similar attributes to care workers. The curve is flat (steep) in regions where there are (are not) several jobs with similar attributes. The proximity function we obtain from the actual data is graphed below in figure 1.

Finally, the normalized proximity weight is given by:

$$\theta_o = \frac{\hat{\theta}_o}{\sum_o \hat{\theta}_o} \tag{7}$$

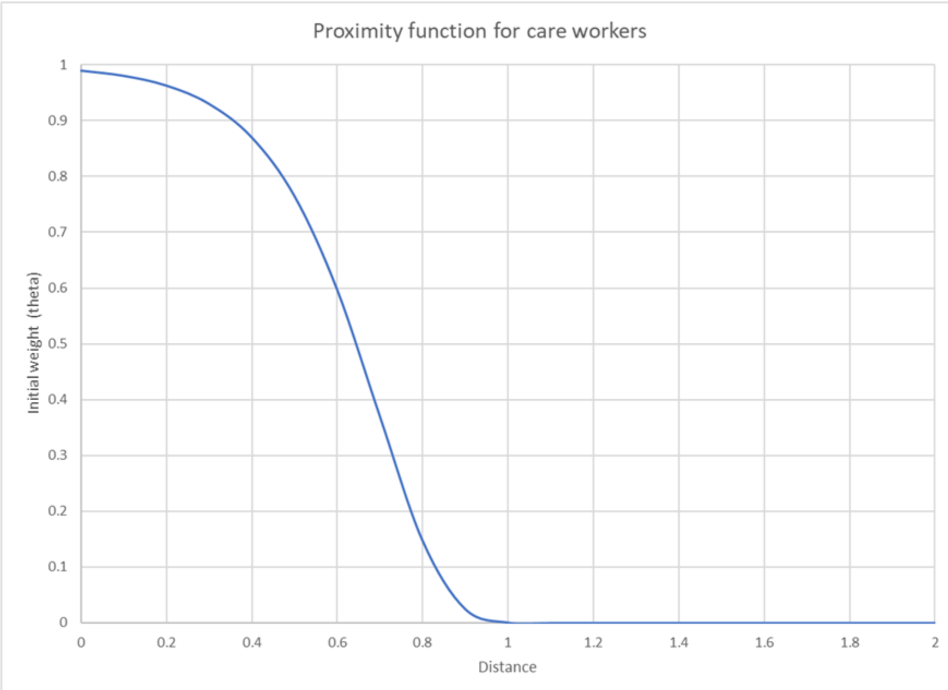

Figure 1: Proximity weight function for care workers

We might note that the weights are pretty stable with respect to our parameter choices.

2.4 Employment and Final Weights

Next, we take an occupation's employment into account. Let $E_{o,a}$ denote employment in occupation o in area a. We define "effective area a employment" in occupation o as a match for the care workers occupation as the product of θ_o and $E_{o,a}$:

$$\hat{E}_{o,a} = \theta_o E_{o,a} \tag{8}$$

"Effective employment" is an increasing function of both employment in occupation o and the proximity-related weight θ_o. Normalizing, the weights $\pi_{o,a}$ in (1) are given by:

$$\pi_{o,a} = \frac{\hat{E}_{o,a}}{\sum_a \hat{E}_{o,a}} \tag{9}$$

3 Results

3.1 Comparable Wage Estimates

We use employment and wage estimates from BLS' OEWS program to calculate the comparable wage for care workers. Column 1 of Table 1 shows the proximity weights as defined by (7) that we obtain for the year 2021 when occupations with different required education levels are assigned a weight of 0. We only show weights that are at least as large as one percent. The occupations in the table have a combined weight of 73.4%; the remaining 26.6% is accounted for by occupations with proximity weights less than 1 percent. As one might expect, psychiatric aides, childcare workers, and orderlies are the occupations with the largest proximity weights.

Column 2 shows the proximity weights we obtain when we do not restrict the set of comparable equation to occupations with the same education. The nursing assistants occupation now has a weight of 17.2 percent, in stark contrast to its weight of 0 when the set of comparable occupations is restricted to occupations with the same required education. The other proximity weights are similar in the two specifications but are a little lower when we do not impose an education match requirement due to the high proximity weight for nursing assistants.

We now use the final weights defined by (9) to calculate the comparable wage for care workers according to equation (1). Table A1 in Appendix A presents 2021 estimates for each state. Column 1 of the table shows total employment in the care workers occupation. Care workers employment is quite large; in 2021, employment was well over three million nationwide. The second column in Table A1 presents the log of the mean care workers wage. Column 3 shows the comparable wage when the set of comparable occupations is not confined to occupations with the same education requirement. And column 4 presents the comparable wage estimate when the set of comparable occupations is restricted to occupations with the same education requirement. As one might expect, the comparable wage estimate is generally larger when comparable occupations are not restricted to occupations with the same education requirement.

Column 5 of Table A1 presents the ratio of the mean care workers wage to the comparable wage when the set of comparable occupations is restricted to occupations with the same education requirement. A ratio less than 1 means that the mean wage of care workers is lower than our estimate of the mean wage for comparable jobs. We will refer to the difference between 1 and the ratio as a wage gap. There is substantial variation in the wage gap among the states, but it is nearly always positive and, in many cases, quite substantial. The gap exceeds 15% in 7 states and the District of Columbia and is quite large at 25% in Louisiana. In contrast,

Table 1: Proximity weights for care workers, with and without education matches

SOC code	**Title**	**Proximity weight with education match (Column 1)**	**Proximity weight without education match (Column 2)**
31-1131	Nursing assistants	0.0%	17.2%
31-1133	Psychiatric aides	9.0%	7.1%
39-9011	Childcare workers	6.8%	5.4%
31-1132	Orderlies	6.2%	4.9%
31-2022	Physical therapy aides	5.4%	4.3%
35-2012	Cooks, institution and cafeteria	5.2%	4.1%
51-9022	Grinding and polishing workers, hand	4.7%	3.7%
35-2015	Cooks, short order	4.2%	3.3%
51-9199	Production workers, all other	3.7%	2.9%
47-2053	Terrazzo workers and finishers	3.5%	2.8%
51-4121	Welders, cutters, solderers, and brazers	3.3%	2.6%
39-2021	Animal caretakers	3.0%	2.4%
35-3041	Food servers, nonrestaurant	2.7%	2.2%
37-2012	Maids and housekeeping cleaners	2.6%	2.0%
45-2093	Farmworkers, farm, ranch, and aquacultural animals	0.0%	1.6%
51-9123	Painting, coating, and decorating workers	1.9%	1.5%
51-2051	Fiberglass laminators and fabricators	1.4%	1.1%
35-9021	Dishwashers	1.4%	1.1%
29-2051	Dietetic technicians	1.4%	1.1%
45-2021	Animal breeders	1.3%	1.0%
51-9192	Cleaning, washing, and metal pickling equipment operators and tenders	1.3%	1.0%
51-6011	Laundry and dry-cleaning workers	1.2%	1.0%
51-2028	Electrical, electronic, and electromechanical assemblers	1.2%	0.9%
39-5011	Barbers	0.0%	0.9%
53-6021	Parking attendants	1.0%	0.8%
51-3023	Slaughterers and meat packers	1.0%	0.8%
	All other occupations	**26.6%**	**22.3%**

the estimated wage gap is approximately zero in Utah and North Dakota. Column 6 presents the ratio of the mean care workers wage to the comparable wage when the set of comparable occupations is not restricted to occupations with the same education requirement. The gaps in column 6 are larger than those in column 5. There are 17 states with a wage gap that exceeds 15%.

Estimates for the nation as a whole are presented in the first row of Table 2. Nationwide, the mean hourly wage for care workers was \$13.92 in 2021. The comparable wage estimate when the set of comparable occupations not restricted occupations with the same required education is \$15.41, implying a wage gap of 9.7%. When the set of comparable occupations is restricted to occupations with the same required education, the comparable wage estimate falls to \$14.76, yielding an estimated wage gap of 5.7%.

Table 2: National comparable wage estimates using OEWS data with SOC codes

Care Workers			**Comparable Workers**			
Mean hourly wage	**Log of mean hourly wage**	**Proximity weight used**	**Mean hourly wage**	**Log of mean hourly wage**	**Care Worker mean wage relative to comparable wage**	**Wage Gap**
\$13.92	2.63	educational matches	\$14.76	2.69	0.94	5.7%
		without educ matches	\$15.41	2.74	0.90	9.7%

3.2 Alternative Comparable Wage Calculation

Armed with the proximity weights (7) obtained from the OEWS, we can use the CPS to estimate the comparable wage for care workers. Specifically, we calculate the comparable wage replacing OEWS wage and employment estimates with those from the CPS but using proximity weights calculated from the OEWS. As shown in Table 3, when comparable occupations are not restricted to occupations with the same education requirement, we obtain a comparable wage estimate of \$16.25. As also shown in the table, the estimate of the mean wage for care workers in the CPS is \$15.30. The resulting wage gap estimate is therefore 5.9%. When comparable occupations are restricted to occupations with the same education requirement, the CPS yields a comparable wage estimate of \$15.78 and thus a wage gap of only about 3.1%.

Comparing the wage gap estimates in the CPS and OEWS, one sees that the wage gap

Table 3: National comparable wage estimates using OEWS and CPS data using the Census occupational classification

	Care Workers			**Comparable Workers**			
Data used	**Mean hourly wage**	**Log of mean hourly wage**	**Proximity weight used**	**Mean hourly wage**	**Log of mean hourly wage**	**Care Worker mean wage relative to comparable wage**	**Wage Gap**
OEWS	\$13.92	2.63	educational matches	\$14.11	2.65	0.99	1.4%
			without educ matches	\$14.78	2.69	0.94	5.8%
CPS	\$15.30	2.73	educational matches	\$15.78	2.76	0.97	3.1%
			without educ matches	\$16.25	2.79	0.94	5.9%

calculated from the CPS is lower than that calculated from the OEWS. This turns out to be partly due to differences in occupational coding between the two surveys. OEWS using SOC occupation codes, while CPS uses the generally less detailed Census codes. As can be seen in Table 3, when we redo the OEWS calculations using Census occupational codes, we obtain a comparable wage estimate of \$14.78 (\$14.11) and an implied wage gap of about 5.8% (1.4%) when comparable occupations are (not) allowed to have a differing educational requirement. These estimates are aligned with those calculated from the CPS data. We prefer the estimates using the more detailed SOC occupation codes.

3.3 Demographic Characteristics

Our estimates indicate a modest gap between the wages that care workers receive and what one might expect given the wages that workers in comparable occupations receive. The care workers occupation tends to be overwhelmingly female. It also has an above average concentration of Black and Hispanic workers as well as immigrants. According to CPS data from 2020 to 2022, the proportions of care workers who were women, Blacks, Hispanics, and immigrants were 82.4%, 26.8%, 23.5%, and 30.5%, respectively. In contrast, in comparable occupations, these proportions were 68.9%, 21.9%, 23.4%, and 22.0%, respectively.

An interesting question is to what extent the wage gap can be accounted for by the demographic characteristics. We use two approaches to estimate this. First, we use the CPS to estimate the proportions of women, Blacks, Hispanics, and immigrants in each comparison occupation and add these to the wage equation (2):

$$ln(\bar{w}_o) = \beta_0 + \sum_{k=1}^{K} \beta_k F_{o,k} + \beta_{K+1} Y_o + \sum_{m=1}^{M} \beta_m^{'} x_{o,m} + \epsilon_o \tag{10}$$

where $x_{o,m}$ is the normalized proportion of workers in occupation o with the m-th demographic characteristic. We then modify the weights in the distance function accordingly:

$$D_o = \frac{1}{K+M+1} (\sum_{k=1}^{K} c_k (F_{o,k} - F_{C,k})^2 + c_{K+1}(Y_o - Y_C)^2 + \sum_{m=1}^{M} c_m^{'} (x_{o,m} - x_{C,m})^2) \tag{11}$$

where $x_{C,m}$ is the proportion of workers with demographic characteristic m in the care workers occupation and:

$$c_k = \frac{|\beta_k|}{\sum_{k=1}^{K+1} |\beta_k| + \sum_{m=1}^{M} |\beta_m^{'}|}, \qquad c_k^{'} = \frac{|\beta_m^{'}|}{\sum_{k=1}^{K+1} |\beta_k| + \sum_{m=1}^{M} |\beta_m^{'}|} \tag{12}$$

As shown in Table 4, controlling for demographic characteristics and using the Census codes, the OEWS estimate of the comparable wage is \$14.61 when the set of comparable occupations is not restricted to occupations with the same required education. When the set of comparable occupations is restricted to occupations with the same required education, the comparable OEWS comparable wage estimate is \$13.79. Recalling that the corresponding estimates when one does not control for demographic characteristics are \$14.73 and \$13.73. Controlling for demographic characteristics thus has very little effect on the estimated comparable wage and wage gap (although when the set of comparable occupations is restricted to occupations with the same required education and when one uses Census occupation codes, the initial small estimated wage gap is eliminated entirely).

Similarly, controlling for demographic characteristics in the CPS has little effect on the estimate of the comparable wage and the wage gap. When comparable occupations are not restricted to having the same education requirement, the comparable wage is \$16.30 when one controls for demographic characteristics and \$16.25 when one does not. And when comparable occupations are restricted to having the same education requirement, the comparable wage is \$15.67 when one controls for demographics and \$15.78 when one does not.

As a second method for estimating the effects of demographic characteristics on the wage gap, we apply the proximity weights obtained from the OEWS to estimate the following weighted

Table 4: National comparable wage estimates using different survey data and proximity weights, controlling for demographics

	Care Workers			Comparable Workers			
Data used	**Mean hourly wage**	**Log of mean hourly wage**	**Proximity weight used**	**Mean hourly wage**	**Log of mean hourly wage**	**Care Worker mean wage relative to comparable wage**	**Wage Gap**
OEWS	\$13.92	2.63	educational matches	\$13.79	2.62	1.01	-0.9%
			without educ matches	\$14.61	2.68	0.95	4.8%
CPS	\$15.30	2.73	educational matches	\$15.67	2.75	0.98	2.4%
			without educ matches	\$16.30	2.79	0.94	6.2%

wage regression using the CPS data:

$$ln(w_i) = \pi_i(\beta_0 + \beta_1 Female_i + \beta_2 Black_i + \beta_3 Hispanic_i + \beta_4 Immigrant_i + \beta_5 Age_i + \beta_6 Educ_i) \quad (13)$$

where $Female_i$, $Black_i$, $Hispanic_i$, and $Immigrant_i$ are variables indicating whether individual care worker i is female, Black, Hispanic, or an immigrant, Age_i and $Educ_i$ corresponds to individual i's age and educational attainment categories and the π_i corresponds to the CPS proximity weight for individual care worker i, which is the product of the CPS estimation weight and the proximity weight determined by (7) above. The comparable wage controlling for demographic characteristics is then simply the predicted wage for individuals in the care workers occupation:

$$ln(\hat{w}_{i \in C}) = \pi_i(\hat{\beta}_0 + \hat{\beta}_1 Female_{i \in C} + \hat{\beta}_2 Black_{i \in C} + \hat{\beta}_3 Hispanic_{i \in C} + \hat{\beta}_4 Immigrant_{i \in C} + \hat{\beta}_5 Age_{i \in C} + \hat{\beta}_6 Educ_{i \in C}) \quad (14)$$

where $ln(\hat{w}_{i \in C})$ is the predicted log wage for care worker i using the model specified above in (13), and $Female_{i \in C}$, $Black_{i \in C}$, $Hispanic_{i \in C}$, $Immigrant_{i \in C}$, $Age_{i \in C}$ and $Educ_{i \in C}$ are the values of the demographic variables for individuals in the care worker occupation. Note that instead of controlling just for a worker's gender, race, and ethnicity, we are also now controlling for their age and adding an additional control for education.[3] As shown in Table 5, the estimated wage gaps are very similar to those obtained by the first method.[4]

[3]Note that education was already at least partly controlled for in our construction of the proximity weights.
[4]Note that our regression predicts the log wage. In the CPS, the mean log care workers wage is 2.66.

Table 5: Care workers mean actual wage vs. mean predicted comparable wage, national estimates

		Log hourly wage			Hourly Wage			
Proximity Weight	**Controlling for demographics**	**Care worker**	**Predicted comparable worker**	**Diff**	**Care worker**	**Predicted comparable worker**	**Diff**	**% Diff**
with educ	No	2.66	2.69	0.03	$14.26	$14.67	$0.41	2.9%
matches	Yes	2.66	2.68	0.03	$14.26	$14.64	$0.38	2.7%
without educ	No	2.66	2.72	0.07	$14.26	$15.23	$0.97	6.8%
matches	Yes	2.66	2.72	0.07	$14.26	$15.25	$0.99	7.0%

4 Conclusion

Home health and personal care aides play an important role in the U.S. health care system, a role that will increase as the population ages. These workers have low education levels and receive low wages. Drawing on the employment and wage information in the OEWS and the information on job attributes in O*NET, we have developed a methodology for estimating what wages in occupations with similar skills and job requirements are paid.

In 2021, the median hourly wage of care workers was just over $14 an hour, according to the OEWS and CPS. The low wage earned by care workers is largely explained by the fact that they are in jobs requiring skills that are not well rewarded in the labor market. However, our results indicate that care workers' wages are somewhat lower than wages in jobs that have similar attributes and require similar skills. When we use the more detailed SOC occupation codes, the OEWS estimates indicate that nationwide care workers' wages are between 6 and 10% lower than the wages in occupations with similar skill requirements. The estimated wage gap is considerably smaller when our calculations are based on the less detailed Census codes found in the CPS data. Besides their low level of education, care workers are disproportionately composed of women, Hispanics, and immigrants. For example, according to the CPS survey between 2020-2022, the percentages of care workers that were females, Hispanics, and immigrants were 82.4%, 23.5%, and 30.5%, respectively. Evidence of the importance of female immigrants, many of whom are Hispanic, is provided by Grabowski, Gruber, and McGarry[4] who find that an increase in their presence in an area reduces the number of nursing home residents, which they argue is due to the fact that immigrants "often work as home health or personal care aides, professions that

Exponentiating yields a mean wage equal to $14.26 (which is less than the straight mean of $15.30 because of the concavity of the log function).

allow older adults to remain in their home longer and at greater levels of disability."[5] We do not find any evidence that the low wage earned by care workers stems from their demographic composition.

Robertson, Sawo, and Cooper have indicated that institutional factors, such as the fact that the majority of care workers are paid through Medicaid's Home and Community Based Services waiver program, may have an important effect on care workers' wages. Possible evidence for this is provided by the fact that our comparable wage and wage gap estimates vary widely among the various states. The wage gap estimates across states range from being quite low to as high as 25 percent.

We are planning to extend the analysis in the paper in two ways. First, wage inequality has been narrowing in recent years.[6] We therefore plan to undertake a pre- and post-pandemic analysis.[7] Second, while our results above indicate that the demographic characteristics of care workers do not explain their low wage, our analysis is based on a comparison of other low wage occupations with similar demographic characteristics. We plan to broaden the set of occupations in our analysis and then re-examine the role played by demographics and job characteristics.

[5]Grabowski, Gruber, and McGarry also find that an increased number of immigrants leads to an increased number of certified nursing assistants.

[6]The trend toward lower wage inequality may have started as early as 2013 and appears to have increased as a result of the pandemic. See Dey Handerker, and Piccone (2022)[3]; Shambaugh, and Strain (2021)[6]; and Autor, Dube, and McGrew (2023)[1]

[7]In this connection, it is worth noting that the OEWS occupational wage and employment estimates we have been using is based on the three years, 2019, 2020, and 2021.

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A Log wage estimates by state

Table A1: Comparable log wage estimates by state

				Comparable log wage estimate		Care worker wage relative to comparable wage	
FIPS	State	Employment (Col. 1)	Log mean wage (Col. 2)	With educ match (Col. 3)	Without educ. match (Col. 4)	With educ. match (Col. 5)	Without educ. match (Col. 6)
22	Louisiana	34,581	2.28	2.57	2.52	0.75	0.79
15	Hawaii	7,784	2.68	2.90	2.91	0.80	0.80
48	Texas	312,192	2.36	2.57	2.62	0.81	0.77
54	West Virginia	17,554	2.38	2.57	2.62	0.82	0.79
11	DC	11,039	2.78	2.97	2.94	0.83	0.85
01	Alabama	19,721	2.35	2.53	2.54	0.83	0.83
51	Virginia	57,670	2.46	2.64	2.67	0.83	0.81
32	Nevada	13,912	2.49	2.67	2.74	0.84	0.78
40	Oklahoma	17,437	2.39	2.55	2.57	0.86	0.84
10	Delaware	8,124	2.54	2.70	2.77	0.86	0.80
37	North Carolina	60,863	2.43	2.59	2.63	0.86	0.82
18	Indiana	37,795	2.52	2.66	2.69	0.86	0.84
26	Michigan	72,001	2.57	2.71	2.76	0.87	0.83
47	Tennessee	28,348	2.45	2.59	2.62	0.87	0.85
20	Kansas	25,361	2.45	2.58	2.63	0.88	0.83
06	California	619,446	2.76	2.89	2.94	0.88	0.84
29	Missouri	72,263	2.51	2.64	2.63	0.88	0.89
39	Ohio	93,583	2.52	2.64	2.68	0.88	0.85
55	Wisconsin	73,319	2.58	2.70	2.76	0.88	0.83
53	Washington	55,165	2.82	2.95	2.92	0.89	0.91
27	Minnesota	108,529	2.68	2.80	2.85	0.89	0.84

Table A1 – *Continued from Previous Page*

				Comparable log wage estimate		Care worker wage relative to comparable wage	
FIPS	**State**	**Employment (Col. 1)**	**Log mean wage (Col. 2)**	**With educ match (Col. 3)**	**Without educ. match (Col. 4)**	**With educ. match (Col. 5)**	**Without educ. match (Col. 6)**
04	Arizona	68,302	2.65	2.77	2.80	0.89	0.87
09	Connecticut	38,997	2.70	2.80	2.84	0.90	0.87
35	New Mexico	32,326	2.50	2.61	2.67	0.90	0.85
45	South Carolina	28,881	2.45	2.55	2.60	0.91	0.86
28	Mississippi	19,468	2.37	2.47	2.49	0.91	0.89
44	Rhode Island	7,430	2.71	2.79	2.83	0.92	0.88
36	New York	487,336	2.78	2.86	2.94	0.92	0.85
05	Arkansas	18,496	2.51	2.59	2.60	0.92	0.92
42	Pennsylvania	199,963	2.58	2.66	2.74	0.93	0.86
23	Maine	15,693	2.72	2.79	2.81	0.93	0.91
12	Florida	69,923	2.52	2.60	2.63	0.93	0.89
41	Oregon	36,051	2.74	2.82	2.88	0.93	0.88
13	Georgia	40,459	2.49	2.57	2.63	0.93	0.87
56	Wyoming	3,806	2.64	2.71	2.76	0.93	0.89
17	Illinois	100,920	2.65	2.72	2.75	0.94	0.91
24	Maryland	31,866	2.66	2.72	2.78	0.94	0.89
08	Colorado	41,076	2.73	2.79	2.81	0.94	0.92
34	New Jersey	65,282	2.70	2.75	2.79	0.96	0.92
31	Nebraska	11,477	2.60	2.64	2.70	0.96	0.90
02	Alaska	6,735	2.82	2.85	2.96	0.97	0.87
33	New Hampshire	7,380	2.68	2.71	2.80	0.97	0.89
25	Massachusetts	113,654	2.86	2.88	2.90	0.98	0.96
16	Idaho	18,300	2.59	2.61	2.65	0.98	0.94
46	South Dakota	3,310	2.62	2.63	2.65	1.00	0.98

Table A1 – *Continued from Previous Page*

				Comparable log wage estimate		Care worker wage relative to comparable wage	
FIPS	**State**	**Employ-ment (Col. 1)**	**Log mean wage (Col. 2)**	**With educ match (Col. 3)**	**Without educ. match (Col. 4)**	**With educ. match (Col. 5)**	**Without educ. match (Col. 6)**
21	Kentucky	24,763	2.60	2.60	2.62	1.01	0.98
30	Montana	8,472	2.63	2.60	2.68	1.02	0.95
50	Vermont	6,523	2.82	2.79	2.81	1.02	1.01
49	Utah	15,647	2.67	2.65	2.68	1.03	0.99
19	Iowa	24,194	2.67	2.63	2.71	1.04	0.96
38	North Dakota	6,260	2.80	2.71	2.81	1.10	0.99