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IZA DP No. 17277

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ABSTRACT

Equal Pay for Better Health: The Health Cost of the Gender Wage Gap*

This paper explores the relationship between gender wage gaps and women's overall health. Using data from the 2011-2019 Current Population Survey, we employ entropy balancing to create comparable samples of men and women and estimate wage gaps for full-time employed working-age women. Adjusting for individual, occupation, and industry characteristics, we estimate the association between wage gaps and self-rated health. Our results suggest that closing the wage gap results in a 1.2 percent reduction in women reporting poor or fair health, equivalent to nearly 170,000 fewer women. These effects are more pronounced for women with below-median wages or in male-dominated jobs.

JEL Classification: F02, F34, F41, G15

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1 Introduction

From 1960 to 1980, women earned 60 percent of what men earned. Over time, this ratio has improved, and women now earn approximately 83 percent (unadjusted) of what men earn. Despite this progress, the gender wage gap remains significant and is estimated to cost women 410,000 dollars over their working lives.[1] While economists have extensively studied the factors contributing to the wage gap, the effect of this gap on women's health is largely unexplored.

In this paper, we aim to address the effect of the gender wage gap on women's health, thereby informing policymakers of a potential additional negative aspect of the wage gap. Specifically, we use census data to estimate the relationship between the gender wage gap and a woman's self-reported health. We find that closing the wage gap would lead to a 1.2 percent decrease in women reporting poor or fair health, translating to nearly 170,000 fewer women. The effect is more pronounced for those earning below the median wage or working in industry-occupation groups with a low representation of women or highly dispersed wages. These findings are especially timely given the current state initiatives to close the pay gap, including passing salary transparency laws, prohibiting employers from asking about prior pay during interviews, and, in some cases, implementing comparable worth laws. These efforts complement Title VII of the Civil Rights Act of 1964, which remains the cornerstone of anti-discrimination law in the US.

A substantial body of health economics literature has examined the impact of income and wealth on health. Much of this research relies on exogenous changes in income, such as lottery winnings, to establish the causal relationship between income and health (e.g., (Apouey and Clark, 2015; Kim and Koh, 2021)). Higher incomes can lead to better health through access to healthier food, improved healthcare, and greater health consciousness.

[1]Center for American Progress, 2022 The Economic, Educational, and Health-Related Costs of Being a Woman https://www.americanprogress.org/article/the-economic-educational-and-health-related-costs-of-being-a-woman/

However, for women, who often earn lower wages, this may translate to working longer hours or multiple jobs to compensate for the wage gap, leading to fatigue, burnout, and less time for self-care activities that promote health. Reverse causality is also possible, as poor health can lead to lower earnings by limiting an individual's ability to work or the types of jobs they can perform.

Income can also indirectly affect health through the gender wage gap. In a review of the literature on gender-based health disparities, Schone (2018) notes that health outcomes for men and women are influenced not only by biology and physiology but also by social and economic factors and individual behaviors. In this paper, we focus not just on income levels but specifically on the gender wage gap. Awareness of wage disparities can create a sense of unfair treatment among women. Associated stress from continued frustration with unequal pay for equal work can affect a woman's health directly through higher cortisol levels, leading to more stress and thus poorer health (Serwinski, Salavecz, Kirschbaum and Steptoe, 2016). Lower earnings relative to men can also reduce women's autonomy and decision-making power within households, limiting their ability to prioritize their health needs. Furthermore, jobs that pay women less relative to men often involve higher stress and poorer working conditions, exacerbating physical and mental health issues. For example, a recent study reports that the wage gap within healthcare occupations is the widest for physicians and advanced practitioners who face high-stress environments (Dill and Frogner, 2024).

In their review of studies on gender inequality and women's health, King, Kavanagh, Scovelle and Milner (2020) conclude that greater gender equality in high-income countries is associated with better health outcomes for women. Similarly, McKetta, Prins, Hasin, Patrick and Keyes (2022) examine the impact of structural sexism, measured by state-level political and economic inequalities, on alcohol use and report higher levels of inequality are associated with higher alcohol use among women. While these studies highlight the broader impacts of gender inequality on women's health, specific research on the gender wage gap's effect on health is limited. To our knowledge, only one prior study has attempted to examine the effect of the gender wage gap on health outcomes. Platt, Prins, Bates and Keyes (2016) use two years of data (2001 and 2002) from a national survey of substance use and other psychiatric disorders to investigate the impact of gender wage gaps on women's mental health. Using propensity score matching, they find that women earning less than comparable men are more likely to experience anxiety and depressive disorders.

To our knowledge, we are the first to provide an in-depth analysis of the effect of gender wage gaps on women's overall health. Using census data from 2011-2019, we analyze a large sample of full-time working men and women aged 25-55. We employ entropy balancing to create gender wage gaps for each woman in our sample by assigning a counterfactual man's wage based on observable characteristics. These wage gaps are then linked to women's self-assessed health, while controlling for a broad array of variables. Recognizing that labor market disparities likely influence industry and occupation choices, we incorporate measures of gender share and wage distribution within industry-occupation groups to assess their impact on the relationship between wage gaps and women's health. Given potential endogeneity concerns, we test the sensitivity of our findings to alternative specifications, including a Bartik-style IV estimator to address potential biases from unobserved factors influencing both wage gaps and health outcomes.

Our findings have important implications for understanding the economic and social determinants of women's health and suggest that policy measures to close wage gaps could offer significant health benefits for women. Addressing economic inequalities is essential for improving public health outcomes, particularly for women who are disproportionately affected by wage disparities.

The remainder of the paper proceeds as follows. Section 2 presents a conceptual framework that guides our estimation. Section 3 describes the data. Section 4 presents our estimation strategy, and the results are presented in Section 5. Section 6 reports sensitivity analysis, and Section 7 explores heterogeneous effects. Section 8 concludes and discusses the main findings.

2 Conceptual Framework

The Grossman model of health demand provides a conceptual framework for isolating the direct and indirect effects of gender pay gaps on health (Grossman, 2000). In the model, an economic agent chooses how to allocate their budget and time over the course of their life, making utility-maximizing choices between investments in home production and their health. A feature of the model is that health is a stock variable that agents can draw upon to make other time investments. However, health depreciates from period to period, and aging raises this depreciation rate.

Gender pay gaps can have both direct and indirect effects on the health of a working woman. A pay gap, by definition, suggests that a working woman is receiving lower pay than a man with similar characteristics. In this way, a gender pay gap acts as a negative income shock for the affected woman, akin to a negative income shock that could arise due to a recession. In the Grossman model, a lower wage constrains the consumer's ability to purchase medical care, which may lead to lower health for a woman relative to a man with similar characteristics.

In the Grossman model of health demand, the indirect effects of gender pay gaps extend beyond lower wages. Two women earning the same wage may experience different levels of perceived wage inequality depending on the gap between their earnings and those of comparable men. Based on Serwinski et al. (2016), Denton, Prus and Walters (2004) and Schone (2018), we expect that earning less than similar men serves as an additional stressor. Such stressors contribute to increased allostatic load, causing a person's health stock to depreciate at a higher rate, similar to accelerated aging (Grossman, 2000). A woman earning less than a man for equal work will need to allocate more resources to health investments (e.g., exercise, medical care) at the expense of other consumption activities to maintain the same level of health. As a result, she may optimally choose poorer health at the margin because the opportunity cost of health investments is higher under a greater allostatic load.

In this framework, the agent chooses optimal health H^* by investing in health (e.g., through medical care purchases) in a given time period, equating the marginal benefit of investments in their health stock and the marginal costs of those investments. This equilibrium condition is typically expressed as the marginal efficiency of capital schedule (MEC), which slopes downwards because there is diminishing marginal product to investments in health (Figure 1), where the marginal costs of health investments are the opportunity costs of not investing in health, the rate of return for other investments (r) and the contemporaneous depreciation rate of the health stock δ.

The depreciation rate δ is treated as exogenous, increasing with age. We argue that δ can also be influenced by a broader set of determinants based on the context around a woman's wage, such as the wages of similar men, gender share in the workplace, wage percentile, and wage dispersion within industry-occupation pairs.

We consider an expression for this depreciation rate δ:

$$\delta = g(wage^m,\ gender\_share,\ wage\_percentile,\ wage\_dispersion), \tag{1}$$

where $wage^m$ is the wage of a similar male counterpart, $gender\_share$ is the share of women in an industry-occupation pair, $wage\_percentile$ represents where a woman's wage falls within her industry-occupation pair, and $wage\_dispersion$ indicates how dispersed wages are within her industry-occupation pair

Based on the literature, we expect that larger wage gaps can lead to elevated stress levels, as women may perceive themselves as undervalued and under-compensated compared to their male counterparts. This stress can manifest as an increased allostatic load, contributing to the faster depreciation of health stock, i.e., higher levels of δ. Gender share, wage percentile, and wage dispersion can also significantly influence δ through higher stress levels. Low gender share in the workplace can result in feelings of isolation; lower wage percentiles are associated with poorer compensation and perceptions of unfairness, while high wage dispersion may heighten the sense of inequity.

By integrating these elements into the Grossman model, we offer a more comprehensive framework for understanding how wage gaps affect women's health. This approach highlights both the direct and indirect pathways through which wage gaps may influence health outcomes and emphasizes the need for targeted policies to address these disparities.

3 Data

3.1 Data Description

We use data from the Current Population Survey's Annual Social and Economic Supplement (CPS ASEC) for our analysis, spanning the period from 2011 to 2019. These data have excellent earnings information, and survey participants are asked about their self-assessed health. Self-assessed health is a commonly used measure of health in empirical economics and has been shown to correlate to morbidity (Mutz and Lewis, 2022; Idler and Benyamini, 1997; Jylhä, 2009). We are aware of no other large nationally representative dataset that has comprehensive labor market information and a measure of health.[2]

We restrict our sample to prime-aged working men and women ages 25 to 55 who

[2]While the CPS provides comprehensive labor market information, it is limited by containing only a single measure of self-rated health. Other datasets, such as the National Health Interview Survey or the Medical Expenditure Panel Survey, also contain measures of earnings and richer measures of health, but the larger sample size in the CPS allows for nationally representative estimates of the effects of wage gaps and sufficient power to estimate industry-occupation-specific effects. The Behavioral Risk Factor Surveillance System survey asks for detailed health equations. However, it only reports household income in categories and has very limited labor market information.

report employment hours greater than or equal to 35 hours a week. We omit observations with missing work hours. We adjust wages to 2019 dollars and then drop observations with real wages greater than or equal to 250,000, removing the right tail of the wage distribution. The final estimation sample contains 136,926 working women.

Self-assessed health is measured on a Likert scale from 1 (poor) to 5 (excellent). We focus on fair or poor health (self-assessed health equal to 1 or 2). Model controls include occupation, industry, usual hours worked per week, health insurance (Medicare, Medicaid, Employer-sponsored health insurance (ESI), veteran status, race/ethnicity, marital status, age, birth cohort, family size, number of children, homeowner, citizen, firm size, limitations on activities of daily living (ADL), and work disability. Unfortunately, the CPS data have no information on work experience, though it is likely co-linear with age, particularly as women's labor force participation continues to resemble that of men. We collapse occupation codes into 22 mutually exclusive categories and industry codes into 13 mutually exclusive categories. To create industry-occupation groups—groupings for each occupation within each industry—we interact industry and occupation dummy variables.

To capture the extent to which a woman is employed in an occupation within an industry dominated by either women or men, we calculate the share of prime-age employees who are women within each industry-occupation pair by taking the weighted mean of women's characteristics from our estimation sample (except without omitting any observations due to extreme wage values). We re-code this gender share into four categories [0-24% women; 25-49%; 50-74%; 75-100%].

We create two additional controls to reflect the distribution of wages within industry-occupation pairs. First, we generate a categorical variable indicating the quartile of the wage distribution in which a woman's wage falls relative to her peers in the same industry-occupation pair. A woman in the first quartile has a wage below at least three-quarters of all men and women in the same industry-occupation pair, whereas a woman in the fourth quartile has a wage above at least three-quarters of all men and women in the same industry-occupation pair. Next, we compute the interquartile range of wages (IQR) in each industry-occupation pair to capture the degree of wage dispersion among workers with similar jobs relative to those in different industry-occupation pairs.

3.2 Descriptive Statistics

Table 1 includes key characteristics of working men and women ages 25-55 from 2011-2019. All of our analyses are weighted to reflect the sampling design of the CPS data. Women earn 78 percent of what men earn (49537.51/63398.55). 4.7 percent of the women in our sample report that their health is fair or poor, which is significantly higher than the 4.1 percent share of men reporting poor or fair health (diff = 0.58 percentage points, 95% CI [0.38, 0.78]). The distribution of age and race is similar across genders, and the rates of health insurance coverage are also comparable. However, women are slightly more educated than men–45 percent of women have a college degree or higher compared to 44 percent of men. At the same time, men tend to work 2 additional hours per week compared to women. Men are also more likely to be married and to be veterans.

4 Estimation Strategy

Our estimation strategy consists of two main steps designed to estimate the effect of gender wage gaps on women's health. First, we employ entropy balancing to calculate wage gaps for each woman in our sample by estimating counterfactual wages, i.e. what women workers would earn if they had the same characteristics and returns to those characteristics as men. Second, we use these estimated wage gaps to analyze their impact on women's self-reported health controlling for a wide range of individual and contextual factors.

4.1 Entropy Balancing: Estimating the Wage Gap

We employ entropy balancing as a data pre-processing method to estimate counterfactual wages for women workers' male counterparts in our sample. This technique constructs a synthetic control group (women) that matches the treatment group (men) on a set of pre-specified covariates. Entropy balancing creates balanced samples by adjusting the weights of units in treatment and control groups based on a set of balance conditions that incorporate information about the covariate moments. This way, we achieve a covariate balance between the two groups on variables that may confound the wage outcome, such as education, marital status, occupation, and industry. The full set of balancing covariates is shown in Appendix Table A2.

Entropy balancing is similar to propensity score matching in that both methods aim to create balanced samples in observational studies with binary treatments. In contrast, unlike the propensity score matching method, which first estimates the weights and then checks the balance, the entropy balancing method works as a reweighting scheme.[3] Entropy balancing avoids the need to specify a functional form or select a matching algorithm for estimating the counterfactual. It does this by finding a set of weights directly from the set of the balancing constraints and does not require continuous adjustments in specifications between different stages. This guarantees that the sample moments in the reweighted control group (women) are precisely equal to the sample moments in the treatment group (men). Unlike other matching methods (e.g., propensity score matching) that may discard observations to achieve balance, entropy balancing retains the entire sample size while adjusting the weights of individual observations.

Operationally, we begin by generating weights from the entropy balancing so that women's covariate distribution looks like men's covariate distribution. Then, we use the

[3] As a robustness check, in Section 6, we re-calculate the wage ratios using propensity score matching.

obtained entropy weights to estimate the following equation:

$$ln(wage_{it}^{m}) = X_{it}^{m}\boldsymbol{\alpha} + \epsilon_{it}, \tag{2}$$

where $ln(wage_{it}^{m})$ is wage of the i^{th} women in year t while using balancing weights obtained for men m. The vector of controls, X_{it}^{m}, includes occupation, industry, citizen status, veteran status, race and ethnicity, marital status, child status, age, birth cohort, education usual hours worked per week, insurance status, disability status, family size, firm size, whether they own their own home, and a constant term. We also control for year and state fixed effects.

The estimated coefficients, $\hat{\boldsymbol{\alpha}}$ represent the returns to characteristics that working-age employed women would receive if they had the same distribution of these characteristics as men. Then, we use these coefficients to calculate the predicted wage, $e^{X_{it}^{f}}$, and plug it into the wage gap equation:

$$wage\hat{\_}ratio_{it} = \frac{e^{X_{it}^{m}\hat{\alpha}}}{wage_{it}}, \tag{3}$$

where the *wage_ratio* is a ratio of what women earn to what they would earn if they had the same characteristics as men. Both the numerator and denominator are measured in dollars.

A wage ratio of 1 implies that there is no gender wage gap, as a reported individual woman's wage matches the predicted wage of a woman who has the same observable characteristics. However, if the wage ratio is above 1, it implies that there is a positive gender wage gap and that a woman with the same observable characteristics has a lower expected wage than a man. The magnitude of the wage ratio reflects the size of the gender wage gap. For instance, a wage ratio of 1.2 implies that a woman with the same observable characteristics as a man would need to increase her wage by 20% to match his wage.

To reduce the influence of extreme estimated wage ratios, we winsorize the sample by omitting observations below the 1st percentile and above the 99th percentile of real wages. This adjustment addresses cases where the fitted value of the man's wage is substantially different from the woman's own wage.

4.2 Effect of Wage Ratio on Health

We proceed to examine the relationship between the estimated individual wage ratios and health using the following model:

$$poor\_health_{it} = \beta_0 + X'_{it}\boldsymbol{\beta} + \gamma \cdot \widehat{wage\_ratio}_{it} + \alpha_s + \delta_t + \varepsilon_{it}, \tag{4}$$

$poor\_health_i$ is an indicator variable equal to one if a person i rated their health as fair or poor in year t and zero otherwise. $\widehat{wage\_ratio}_{it}$ is derived in Section 4.1 and represents the ratio of what a woman earns to what she would earn if she had the same characteristics as a man. X'_{it} is a vector of individual-specific controls such as occupation, industry, usual hours worked per week, health insurance (Medicare, Medicaid, ESI–employer-sponsored insurance), veteran status, race/ethnicity, marital status, age, birth cohort, family size, number of children, homeowner, citizen, veteran, education, firm size, limitations on activities of daily living (ADL) & whether a disability prevents one from working. α_s and δ_t are state and year fixed effects to control for unobservable time-invariant state-specific characteristics and common time trends.

The relationship between wage ratios and health may exhibit heterogeneity depending on contextual factors within an industry-occupation pair. Some of these factors include the share of women workers, the woman's wage relative to her peers, and the dispersion of wages. We hypothesize that the gender wage gap may have a more detrimental effect on health for women in traditionally male-dominated industry-occupation groups, as they may encounter more discrimination, harassment, or isolation compared to those in gender-balanced or women-dominated groups. Additionally, women with wages in the lower percentile compared to their peers may experience greater stress and adverse health effects due to poorer compensation and perceptions of unfairness; and high wage dispersion within an industry-occupation pair can further heighten the sense of inequity and contribute to increased stress and negative health outcomes for women.

We consider these contextual factors by interacting wage ratios with measures of gender share, wage quartile, and the interquartile range of wages within an occupation-industry pair:

$$\begin{aligned} poor\_health_{it} = \beta_0 + X_{it}'\boldsymbol{\beta} + \gamma_1 \cdot wage\_gap_{it} + \gamma_2 \cdot ind\_occ\ factor_{it} + \\ + \gamma_3 \cdot wage\hat{\_}gap_{it} \times ind\_occ\ factor_{it} + \alpha_s + \delta_t + \varepsilon_{it}, \end{aligned} \tag{5}$$

where $ind\_occ\ factor_{it}$ is an industry occupation-specific measure such as the share of women employees, the quartile of women's wages relative to all wages, or the interquartile range of wages. We estimate the industry-occupation-specific marginal effect of wage gaps on health as $\hat{\gamma}_1 + \hat{\gamma}_3 \cdot ind\_occ\ factor_{it}$ for each industry-occupation pair.

5 Results

To understand the factors influencing wage differences between men and women, we examine the returns to various characteristics. Appendix Table A1 shows the coefficients obtained from estimating equation (2) after entropy weighting women's covariates to those of similar men. The returns to a college education or an advanced degree are higher for women but the return to the lower levels of education are greater for men. Whites of either gender earn more than their Black or Hispanic counterparts. The return to marriage is three times higher for men, reflecting the strength of the male marriage premium. The returns to age and work hours are similar for men and women. In the appendix Table A1 in parts 2 and

3, we show the returns to the different occupation and industry categories, which are also included in this regression.

Using equation (3), we calculate estimated wage ratios by comparing the fitted wages for women from equation (2) to their actual wages. Table 2 presents the estimated wage ratios. The mean wage ratio is 1.08, indicating that, on average, a working man with the same observable characteristics as a working woman is predicted to earn 8% more. Figure 2 shows the kernel density of the ratio of men's to women's earnings after winsorizing the sample. The distribution is skewed to the right, with 5.8% of observations with estimated wage ratios at or above 2.

Table 3 presents the estimated marginal effects of wage ratios on reporting poor or fair health from equation (4). In the unadjusted model, column (1), a one-unit change in the wage ratio is associated with a 0.012 increase in the likelihood of reporting poor or fair health. This effect can be interpreted as a 100 percentage point increase in the wage ratio is associated with a 1.2 percentage point reduction in the likelihood of reporting poor or fair health.

An instructive way to interpret the scale of this effect is to consider fully eliminating the gender wage gap. Using the mean entropy-weighted wage ratio of 1.08 and the sample average rate of poor/fair health of 4.7% among women, an estimated coefficient of 0.012 suggests that fully closing the wage gap would lower the likelihood of a woman having poor or fair health by 0.096 percentage points (0.012*0.08 = 0.00096), a 2.04 percent reduction (0.00096/0.047=0.0204). In our sample, 4.7 percent of women report their health as fair or poor, which is significantly higher than the 4.1 percent of men reporting poor or fair health (diff = 0.58 percentage points, 95% CI [0.37, 0.78]). Relative to this gender health gap in the likelihood of reporting poor or fair health, the 0.096 percentage point change in the likelihood associated with closing the wage gap would close 16.6% of the health gap (0.00096/0.0058 = 0.1655; 95% CI [12.2%, 21.5%]).

Columns (2) and (3) present the estimated marginal effect after adding state and year fixed effects. The results do not change. Adding individual-level controls in column (4) also leaves the results unchanged. Only, after including our constructed measures of industry-occupation characteristics, column (5), the estimated coefficient on wage gaps falls to 0.007, though it is still statistically significant. We do not find significant associations between gender share or the IQR of wages within industry-occupation pairs and self-rated health. We do estimate a statistically significant association between a woman's quartile of wage and health, with women in higher wage quartiles significantly less likely to report poor or fair health relative to the bottom quartile of wages within the industry-occupation pair.

Interpreting the 0.007 coefficient from the fully adjusted model in terms of closing the gender wage gap can provide meaningful insights. Using the entropy-weighted wage ratio of 1.08 and the sample average rate of poor/fair health of 4.7% among women, this coefficient suggests that fully closing the wage gap would lower the likelihood of a woman having poor or fair health by 0.056 percentage points (0.007*0.08 = 0.00056), a 1.2 percent reduction (0.00056/0.047=0.012). Based on CPS sample weights, 14.1 million prime-age working women are estimated to report poor or fair health. A 1.2 percent decrease would translate to nearly 170,000 fewer women in poor or fair health. Furthermore, relative to the observed gap in the likelihood of having poor or fair between men and women, a 0.056 percentage point reduction in the likelihood a woman worker is in poor or fair health would narrow the gender health gap by 9.7% (0.00056/0.0058 = 0.097; 95% CI [5.2%, 15.0%]).

6 Sensitivity Analysis

6.1 Alternative Matching

We check the robustness of our results by comparing our main estimates, which use entropy weighting, to two alternative approaches for estimating wage gaps: (1) using no matching weights, (2) using propensity-score nearest neighbor matching.

For the approach with no matching weights, we estimate equation (2) using only the fitted wage for the male counterpart, without any adjustments to balance the sample characteristics. Using this alternative measure of the wage gap, we re-estimate our main specification, equation (4). The results are presented in column (1) of Table 4. We find a slightly smaller, though still statistically significant coefficient of 0.006, which is in line with the results presented in column (5) of Table 3.

For the propensity-score nearest neighbor matching approach, similar to Platt et al. (2016), we use the full slate of controls in equation (2) to propensity score match women to men with the most similar observed characteristics. Then, we use the wage of the matched male counterpart as the counterfactual wage when computing the wage ratio in equation (3). The results are presented in column (2) of Table 4. The estimated coefficient of the wage gap on health (0.007) is the same as the results from entropy weighing presented in column (5) of Table 3.

6.2 Selection Into Industry and Occupation

If selection into specific jobs (some having higher wage ratios than others) is conditionally independent of health based on observed characteristics, then our estimates remain unbiased. However, women may choose occupations based on their health or to gain a health benefit. For example, a woman may select a particular job due to a generous family leave policy or health insurance offer. In some cases, women may accept lower pay in exchange for these fringe benefits (Blume-Kohout, 2023).

While the association between health and selection into lower-paying work does not inherently bias our estimates, if this selection is linked to jobs with higher or lower wage ratios, we might overstate or understate the effect of gender pay gaps on health. Additionally, women might select certain jobs because they have a health condition and the occupation can accommodate their health needs. Because we can only control for a worker's industry-occupation pair, selection into specific occupations within industries may introduce bias.

To some extent, we address these concerns through additional *within* industry-occupation controls such as wage quartile and variance of wages, which can capture the degree to which women choose lower-paying or more flexible work within an industry-occupation group. However, this may not fully mitigate potential selection bias. For example, although we compare men and women within the same industry-occupation group, Goldin (2014) shows that women may select into different work niches within an occupation to obtain flexible schedules or other non-wage benefits. Additionally, other biases might arise, including unobserved factors affecting both the wage ratio and health (e.g., genetics, personality, or preferences), measurement error from using self-reported wages, and reverse causality, as health may affect the wage ratio through productivity or labor supply.

In the following subsections, we present two ways to address the impact of selection. First, we employ a Bartik-style shift-share instrument using temporal shifts in employment growth across industry-occupation groups to create exogenous variation in wage ratios. Second, we assess the impact of the Affordable Care Act on selection into industries or occupations by estimating separate models for pre-ACA (2011-2013) and post-ACA (2015-2019) periods.

6.2.1 Shift-Share Design

OLS estimates of the effect of wage gaps on health may be downward biased because latent factors that attenuate comparisons, such as non-work related accidents and illness, can explain reported poor or fair health, especially if these are similarly likely to occur across low and high wage gap workers. Likewise, OLS could be biased downward if women select lower-paying work based on their own health or time preference, leading to women with high wage gaps and better health - attenuating the overall effect. Conversely, women in poor health may select lower-paying work in exchange for defined health insurance benefits or time flexibility, potentially biasing OLS upwards.

We do not know of any instrumental variable (IV) that can exogenously shift gender wage ratios that would not also affect a woman's health. However, we can use the temporal shifts in the employment growth of different industries-occupation groups as a Bartik-style shift-share instrument. This is a common research method that predicts the current values of an endogenous variable (such as individual wage ratios) by using lagged (or fixed) stocks of a variable at the regional level (in our case, the region is industry-occupation shares) and aggregate flows of another variable (such as average wage ratios). Increases in the share of a given industry-occupation group suggest greater labor demand within that group, which should lead to higher wages. The effect of overall wage growth on wage gaps is ambiguous; however, changes in wage gaps due to the effects of industry-occupation group growth on wages are plausibly exogenous. The ambiguity stems from the potentially differential wage response to changing labor demand between men and women, which could widen, narrow, or preserve existing wage gaps.

A limitation of IV estimates of the effect of wage gaps on health is that the effect is local only to women where the shift shares affect the wage ratios. Conceptually, wage gaps in industry-occupations groups with static shares may have significant effects on the health of women in those jobs but will not be reflected in the IV based on a shift-share design. Despite this limitation, IV estimates of the effect of wage gap ratios on women's health are free from confounding due to simultaneity and omitted variable bias.

To implement the shift-share design, we first compute the average wage ratios within each industry-occupation group for each observation in our sample, excluding that woman's own wage ratio from the group average. Next, we compute the national industry-occupation shares in 2011–the first year of our data. Finally, we calculate the Bartik-style instrument as the weighted average of the wage ratios, using the 2011 industry-occupation shares and the corresponding average-industry occupation wage ratios. The identifying assumption is that the initial industry-occupation composition is unrelated to subsequent shocks to wage gaps after controlling for other factors. The nationwide growth rates serve as shifts in labor demand external to any industry-occupation group.

The results are presented in Table 4, column (3). The first stage F-statistic is 44.3, which suggests that the instrument is predictive of women's wage ratios. The IV estimate for the effect of wage ratios on women's health is 0.012 (p=0.001).While the magnitude of the estimated effect is larger than our main result, it has a somewhat different interpretation. This estimate measures the effect of wage gaps on health for women in industry-occupation groups that experienced changes in their employment shares. These changes in employment shares led to wage changes, which in turn affects wage gaps. Thus, the IV estimate captures how these externally driven changes in wage gaps influence women's health. This leads to differing identifying variations in the wage gap.

It is worth noting that from an economic standpoint, the effect sizes are not as different as they appear—their confidence intervals overlap—the lower bound of the IV confidence interval overlaps with the upper bound of the OLS confidence interval from column (5) of Table 3. The actual percentage effects are of a similar order of magnitude. Relative to the gender gap in the likelihood of reporting poor or fair health observed in our sample, the IV estimate expressed as a percentage point change in the likelihood associated with closing the wage gap would close 16.6% of the gender health gap, compared with 9.7% based in the OLS estimate.

6.2.2 Variation in Selection on Health Benefits from Affordable Care Act

Selection into particular industries or occupations driven by health insurance offers depends partly on the availability of alternative sources of coverage. Provisions of the Affordable Care Act (ACA), for instance, subsidized the purchase of individual private plans on state-based marketplaces while also mandating that most large employers offer health insurance as a benefit. To assess the sensitivity of our results to possible unobserved selection, we estimate separate models using our main specification on subsets of data from before the implementation of most ACA provisions (2011-2013) and after implementation (2015-2019), omitting 2014 due to the initial adoption of provisions like Medicaid Expansion during that year.

A limitation of this split-sample analysis is that the time periods before and after the implementation of many provisions of the ACA may not be directly comparable due to changes in economic conditions, health insurance markets, and employer behaviors. Additionally, the gradual nature of ACA implementation and varying adoption rates across states may further complicate the interpretation of results from this before-and-after comparison. Despite these limitations, this analysis provides insight into how changes in health insurance availability may affect selection patterns in industries and occupations.

Columns (4) and (5) of Table 4 present the estimated coefficients from pre- and post-ACA respectively. We find that higher wage gap ratios are associated with larger increases in the likelihood of poor or fair health for women in the years before the ACA compared to after. However, we find a similar magnitude effect in the post-ACA period as our overall effect pooled across years. This suggests that, while there may be some bias due to selection in our data, this selection likely does not explain all of the estimated relationship between wage gap ratios and health.

Our results are robust and consistent. In this section, we have measured associations after several attempts to eliminate bias due to selection that may explain the total effect. We consistently find a positive and significant association between the presence of a higher wage gap and poorer health for women workers, which tends to be of a similar magnitude. This provides us with reassurance about the reliability of our conclusions.

7 Heterogeneity of Effects of Wage Ratios

To explore potential heterogeneity in the effects of wage gaps on women's health, we examine whether the relationship varies with contextual factors within an industry-occupation pair. Following equation (5), we interact wage ratios with measures of gender share, wage quartile, and the interquartile range of wages within occupation-industry pairs. Table 5 presents the estimated marginal effects of the wage ratio interacted with each of these contextual factors. These effects are estimated in three separate models, with each model allowing for a different interaction specification.

The first panel of Table 5 shows the estimated associations between wage ratios and the likelihood of poor or fair health, evaluated at different values of the share of women workers within an industry and occupation pair. The association between wage ratios and women's health is stronger when the share of women workers in an industry-occupation pair is lower. Figure 3 shows the estimated marginal effects of wage ratios from the interacted model across the full range of gender shares, alongside the distribution of women in industry-occupation pairs for each level of gender share. We observe a wide variety of gender shares across industry-occupation pairs, ranging from 10-90% share of women. The association between wage gap ratios and health is declining in the share of women and is statistically significantly different from 0 except when the share of women exceeds 80% within the industry-occupation pair.

The second panel of Table 5 contains the estimated associations between wage ratio and the likelihood of poor or fair health evaluated at quartiles of all workers' wages within an industry-occupation pair. Figure 4 shows the estimated margins from this model overlayed with the share of women in each wage quartile within their industry-occupation pair. The majority of women have wages below the median wage within their industry and occupation, and wage gap ratios only have a significant association with women's health when their wages are below the median wage within an industry occupation pair.

The third panel contains the estimated associations between the wage ratio and the likelihood of poor or fair health, evaluated at distinct values of the interquartile range (IQR) of all workers' wages within an industry-occupation pair. Figure 5 shows the estimated marginal effects. The association between wage ratios and poor health increases with the dispersion of wages within a woman's industry and occupation. These associations are statistically significant across most of the IQR values for the majority of industry-occupation pairs in our sample.

8 Discussion and Conclusion

Wage gaps, which have been a persistent feature of the US economy can affect health through multiple pathways. Lower wages, can impede access to medical care, or impose a direct negative effect on budgets and utility. Moreover, wage gaps can lead to stress from perceptions of being undervalued by employers or unfavorable comparisons with peers' wages.

This paper explores the relationship between gender wage gaps and women's health. After adjusting for individual, state, year, industry, and occupation characteristics, we find that closing all wage gaps would be associated with a 1.2 percent reduction in the number of women reporting poor or fair health. This average effect translates into significant changes in population health. Using the CPS sample weights, we estimate that 14.1 million prime-age working women report poor or fair health. Reducing this rate by 1.2 percent would mean nearly 170,000 fewer women in poor or fair health.

We explore direct and indirect pathways by including measures of gender share and wage distributions in each industry-occupation pair. A lower gender share in the workplace exacerbates negative health impacts, possibly due to increased feelings of isolation and discrimination. Being in a lower wage quartile is also associated with more negative effects, indicating that wage gaps impose greater harm when a woman's wage is lower. Finally, higher wage dispersion further intensifies negative effects, as variability in wages can lead to greater perceived inequity and stress among women workers.

There are some limitations to our analysis. While we employ a rich set of controls from the CPS, our wage equations rely on only characteristics of workers observed in the CPS, and actual wage gaps may be explained in part by unobservable factors that may further favor male workers. Additionally, the CPS limits us to only one measure of health, though single-item perceived health status is a validated measure of underlying health commonly used in behavioral health studies.

Despite these limitations, our study provides important insights. This paper is the first to estimate the effect of wage gaps on overall health and employs a modeling approach that allows for separate identification of the direct and indirect pathways through which wage gaps might affect health. We find that the effect of wage gaps on health is non-trivial and that closing the gender wage gap would be associated with a significant improvement in women's health.

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Figure 1: Marginal Efficiency of Health Capital.

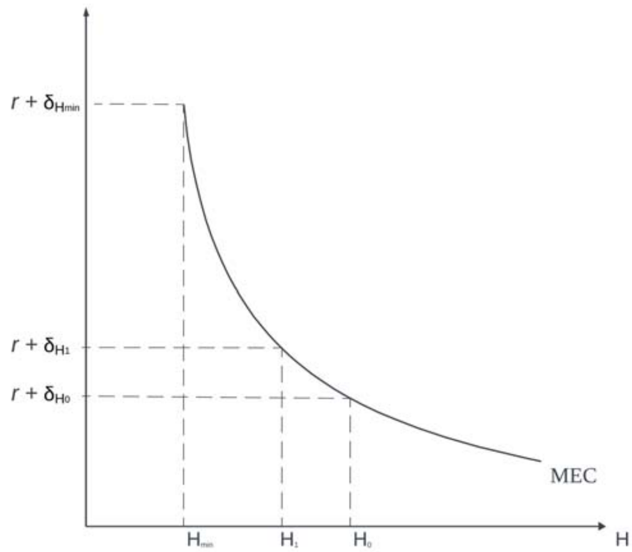


Figure 2: Kernel Density of the Wage Ratio.

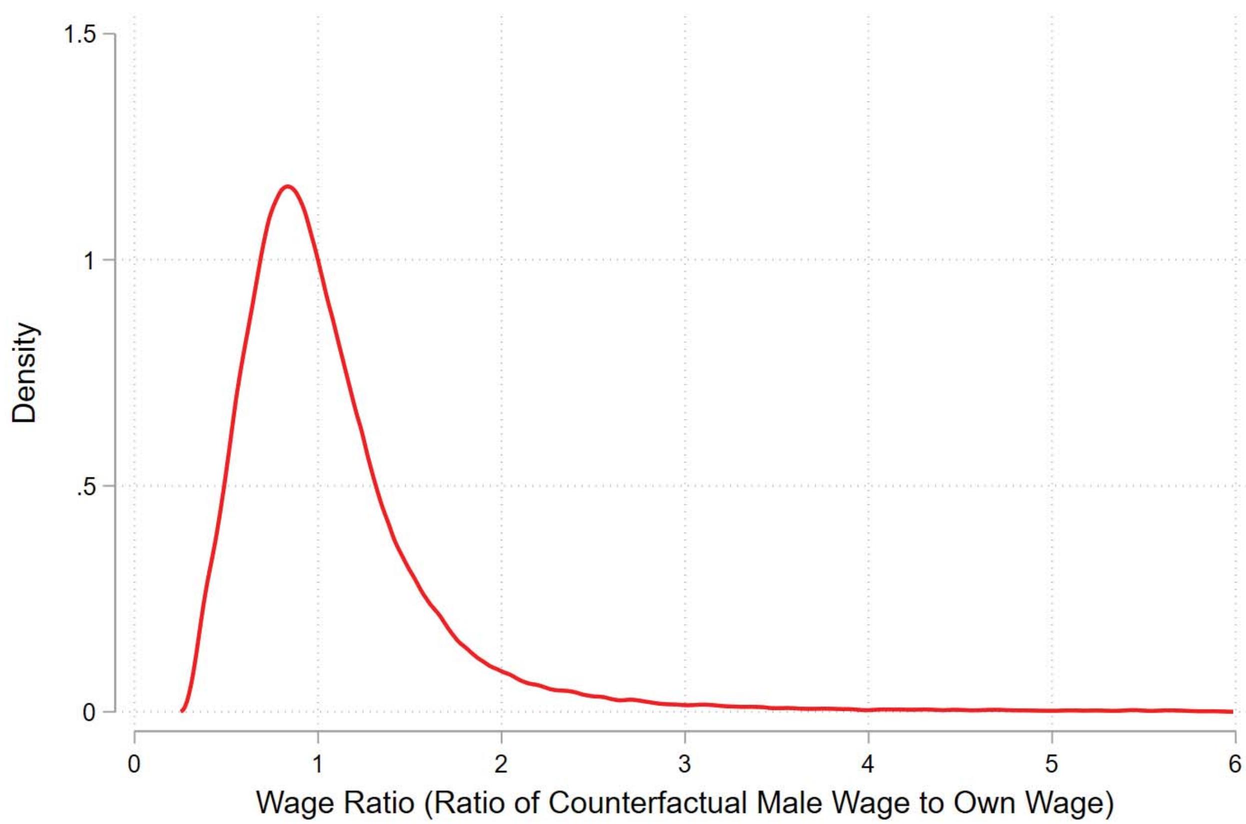
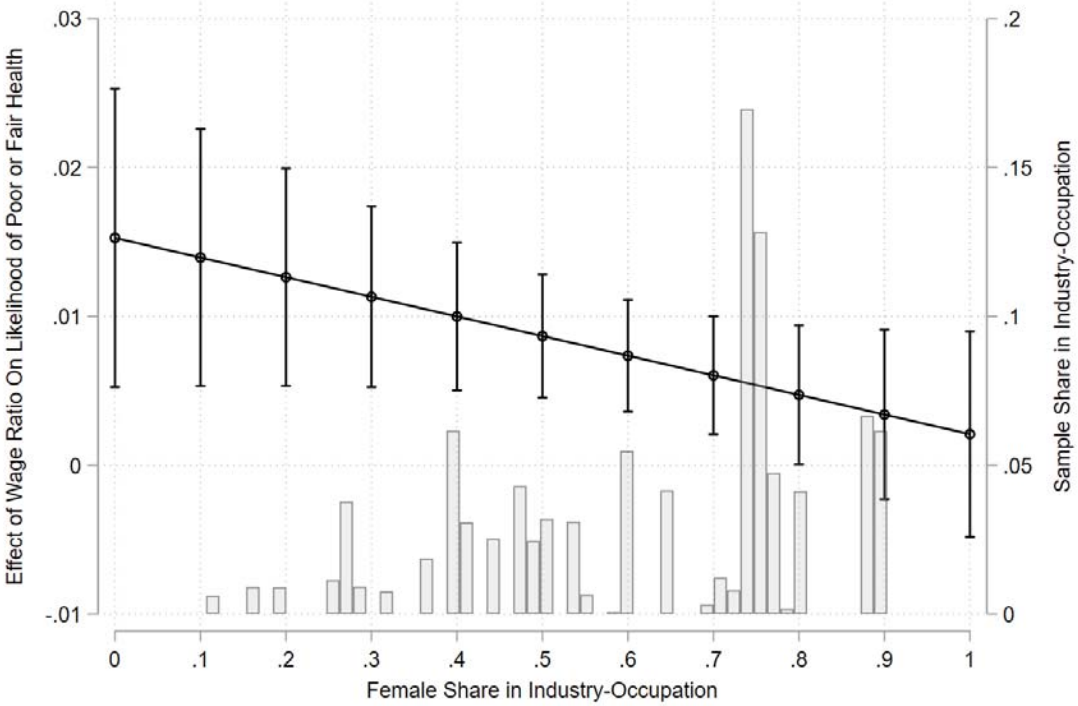
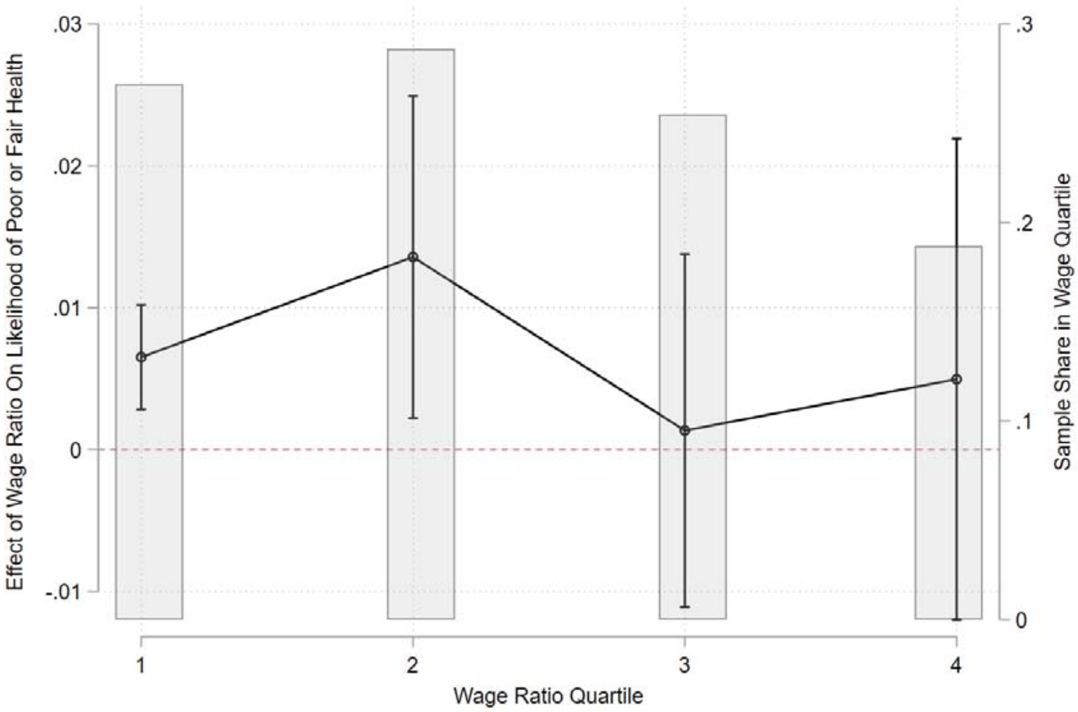


Figure 3: Effect of Wage Gaps on Employed Working Age Women's Likelihood of Self-rated Poor or Fair Health By Share of Women in an Industry-Occupation Pair.



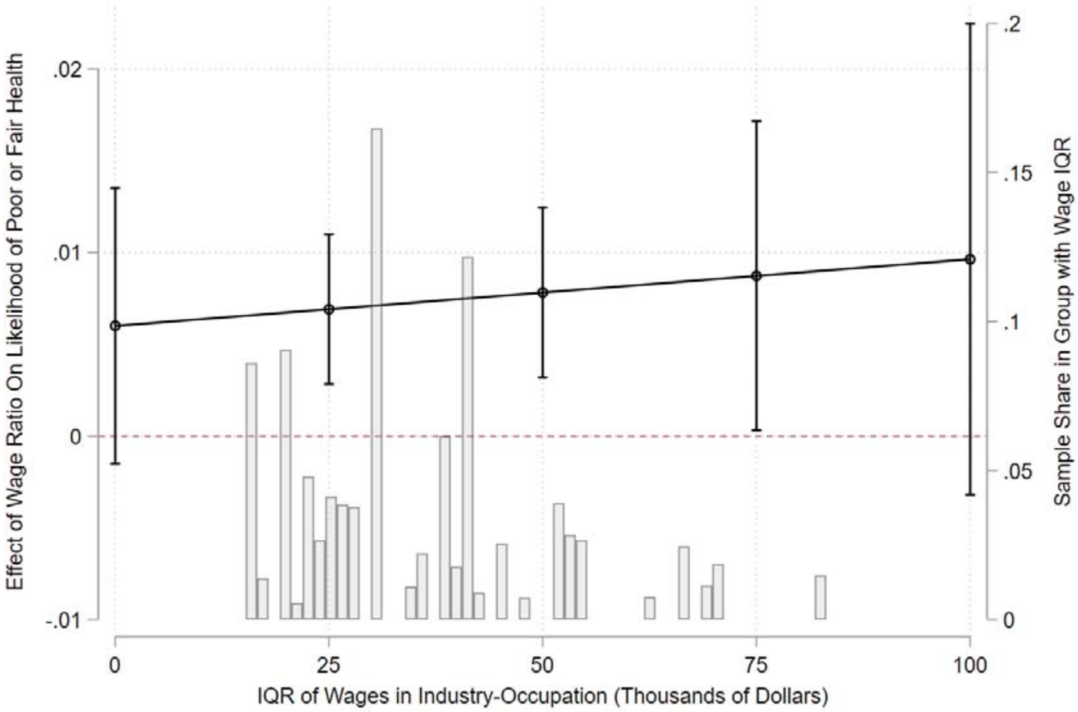
Notes: Estimated marginal effects are from a model where wage ratio is interacted with the share of women each woman's industry-occupation group. The sample contains women who are full-time employed (35+ hours/week) ages 25 to 55 with non-missing data. Model controls include occupation, industry, usual hours worked per week, health insurance (Medicare, Medicaid, ESI), veteran status, race/ethnicity, marital status, age, birth cohort, family size, number of children, homeowner, citizen, education, firm size, ADL & work disability. We cluster by industry-occupation groups and removed all industry-occupation groups that have less than 100 women. The histogram bars show the share of the sample of women in an industry-occupation with a given share of women workers.

Figure 4: Effect of Wage Gaps on Employed Working Age Women's Likelihood of Self-rated Poor or Fair Health By Quartile of all Workers' Wages in an Industry-Occupation pair.



Notes: Estimated marginal effects are from a model where wage ratio is interacted with the within industry-occupation quartile of each woman's wage. The sample contains women who are full-time employed (35+ hours/week) ages 25 to 55 with non-missing data. Model controls include occupation, industry, usual hours worked per week, health insurance (Medicare, Medicaid, ESI), veteran status, race/ethnicity, marital status, age, birth cohort, family size, number of children, homeowner, citizen, education, firm size, ADL & work disability. We cluster by industry-occupation groups and removed all industry-occupation groups that have less than 100 women. The histogram bars show the share of the sample of women whose wage falls withing each within industry-occupation quartile.

Figure 5: Effect of Wage Gaps on Employed Working Age Women's Likelihood of Self-rated Poor or Fair Health By Inter-Quartile Range of Worker's Wages in an Industry-Occupation Pair.



Notes: Estimated marginal effects are from a model where wage ratio is interacted with the inter-quartile range (IQR) of wages within that worker's industry-occupation group. The sample contains women who are full-time employed (35+ hours/week) ages 25 to 55 with non-missing data. Model controls include occupation, industry, usual hours worked per week, health insurance (Medicare, Medicaid, ESI), veteran status, race/ethnicity, marital status, age, birth cohort, family size, number of children, homeowner, citizen, education, firm size, ADL & work disability. We cluster by industry-occupation groups and removed all industry-occupation groups that have less than 100 women. The histogram bars show the share of the sample of women in an industry-occupation with a given IQR of wages.

Table 1: Weighted Population Characteristics of Working Men and Women aged 25-55, 2011-2019

	Men		Women	
	Mean	**S.D.**	**Mean**	**S.D.**
Annual Wage	63,398.55	40,655.63	49,537.51	30,883.19
Self-Rated Health Poor or Fair	0.041	0.198	0.047	0.211
Age				
Age 25 to 29	0.16	0.37	0.16	0.37
Age 30 to 39	0.33	0.47	0.31	0.46
Age 40 to 49	0.32	0.47	0.33	0.47
Age 50 to 55	0.19	0.39	0.21	0.40
Birth Cohort				
Born 1947-1956	0.003	0.05	0.003	0.06
Born 1957-1966	0.22	0.41	0.24	0.43
Born 1967-1976	0.32	0.47	0.32	0.47
Born 1977-1986	0.33	0.47	0.31	0.46
Born 1987-1996	0.13	0.34	0.13	0.33
Race/Ethnicity				
Non-Hispanic White	0.63	0.48	0.62	0.48
Non-Hispanic Black	0.11	0.31	0.14	0.35
Hispanic	0.16	0.37	0.15	0.36
AAPI	0.08	0.28	0.07	0.26
Other/Multiple Race	0.01	0.11	0.01	0.11
Education				
Less Than HS Diploma	0.05	0.22	0.03	0.18
HS Diploma	0.26	0.44	0.22	0.42
Some College	0.25	0.43	0.30	0.46
College Degree	0.28	0.45	0.28	0.45
Advanced Degree	0.16	0.37	0.17	0.38
Employer Sponsored Health Insurance	0.62	0.48	0.59	0.49
ESI Status Missing	0.23	0.42	0.27	0.45
Medicaid	0.05	0.21	0.05	0.23
Medicare	0.002	0.04	0.002	0.04
Veteran	0.08	0.28	0.02	0.12
Citizen	0.80	0.40	0.85	0.36
Married	0.62	0.49	0.57	0.49
Number of Children	1.04	1.22	1.06	1.14
Homeowner	0.66	0.47	0.67	0.47
Usual Weekly Work Hours	44.40	8.19	42.00	6.26
Share of Women in Industry-Occupation Pair	0.43	0.20	0.63	0.20
Wage Interquartile Range in Industry/Occupation	39,247	16,099	35,223	15,111
Quartile of Wage in Industry/Occupation				
1st Quartile	0.17	0.38	0.27	0.44
2nd Quartile	0.24	0.43	0.29	0.45
3rd Quartile	0.28	0.45	0.25	0.44
4th Quartile	0.31	0.46	0.19	0.39
Observations	113,797		136,926	

Notes: All wages in 2019 US dollars. Sample is individuals who report working 35+ hours per week. Descriptives for ADL/presence of a disability, family size, firm size, industry and occupation categories are not shown.

Table 2: Estimated Wage Ratios for Prime Age Working Women, 2011-2019

	Observations	Mean (SD)	Median	IQR
Full Sample				
Wage Gap Ratio	139,651	2.04 (55.65)	0.95	0.73 - 1.26
Winsorized Sample				
Wage Gap Ratio	136,926	1.08 (0.58)	0.95	0.73 - 1.25

Notes: Wage gap ratios are constructed as the ratio of the counterfactual male employee wage from entropy-weighted wage equations to the woman's own wage. IQR = Interquartile range. All wages in 2019 US dollars. Winsorized sample omits observations with wage gaps below the 1st percentile and above the 99th percentile.

Table 3: Effect of Wage Gaps on Employed Working Women's Likelihood of Poor or Fair Self-Rated Health

	(1)	(2)	(3)	(4)	(5)
Wage Gap (Ratio to Own Wage)	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Year FE		X	X	X	X
State FE			X	X	X
CPS Controls				X	X
Share of women in Occ/Ind [0,1]					-0.016
					(0.014)
Quartile of wage in Occ/Ind					
2nd quartile					-0.006^{**}
					(0.003)
3rd quartile					-0.009^{**}
					(0.003)
4th quartile (highest)					-0.011^{***}
					(0.003)
IQR of Wages in Occ/Ind [$1,000]					0.000^{*}
					(0.000)
Constant	0.034^{***}	0.038^{***}	0.042^{***}	0.045^{***}	0.072^{***}
	(0.003)	(0.004)	(0.008)	(0.015)	(0.019)
Observations	136,926	136,926	136,926	136,926	136,926

Notes: Sample contains women who are full-time employed (35+ hours/week) ages 25 to 55 with non-missing data. Model controls include occupation, industry, usual hours worked per week, health insurance (Medicare, Medicaid, ESI), veteran status, race/ethnicity, marital status, age, birth cohort, family size, number of children, homeowner, citizen, education, firm size, ADL & work disability. Share of women in industry-occupation group and below median wage are constructed in the sample for every industry and occupation pair. We cluster by industry-occupation groups and removed all industry-occupation groups that have less than 100 women. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Alternative Specifications and Sensitivity Analyses

	(1) No Selection Weight	(2) Propensity Score	(3) Bartik IV	(4) Pre-ACA (2011-2013)	(5) Post-ACA (2015-2019)
Wage Gap (Ratio to Own Wage)	0.006***	0.007***	0.012***	0.013***	0.004**
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Year FE	X	X	X	X	X
State FE	X	X	X	X	X
CPS Controls	X	X	X	X	X
Share of women in Occ/Ind [0,1]	−0.016	−0.016	−0.003	−0.102	
	(0.014)	(0.014)	(0.006)	(0.020)	(0.023)
Quartile of wage in Occ/Ind					
2nd quartile	−0.006**	−0.006**	0.002	−0.005	−0.007*
	(0.003)	(0.003)	(0.006)	(0.004)	(0.003)
3rd quartile	−0.009***	−0.009***	0.002	−0.007	−0.009**
	(0.003)	(0.003)	(0.008)	(0.005)	(0.004)
4th quartile (highest)	−0.012***	−0.012***	0.002	−0.011*	−0.012***
	(0.003)	(0.003)	(0.010)	(0.006)	(0.004)
IQR of Wages in Occ/Ind [$1,000]	−0.0001*	−0.0001*	−0.0002***	−0.0003*	−0.0003
	(0.000)	(0.000)	(0.0001)	(0.0002)	(0.0002)
Constant	0.074***	0.073***	0.061***	0.066***	0.041**
	(0.019)	(0.019)	(0.016)	(0.026)	(0.019)
First-stage F-Stat			44.33		
Observations	136,926	136,968	136,926	47,947	73,230

Notes: Sample contains women who are full-time employed (35+ hours/week) ages 25 to 55 with non-missing data. Model controls include usual hours worked per week, health insurance (Medicare, Medicaid, ESI), veteran status, race/ethnicity, marital status, age, birth cohort, family size, number of children, homeowner, citizen, firm size, ADL & work disability. Share of women in the industry-occupation group and below median wage are constructed in the sample for every industry-occupation pair. All models include occupation and industry except Column 3. The sample size in column 2 results from different percentile cuts from winsorizing on the estimates wage gap ratios from propensity score matching. Estimates in column 3 employ temporal shifts in the employment growth of different industries-occupation groups as a Bartik-style shift-share instrument for the estimated wage gap ratio. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of Wage Gaps on Employed Working Women's Likelihood of Self-rated Poor or Fair Health By Industry-Occupation Characteristics

	Marginal Effect
Share of Women Workers in Ind/Occ	
25% Female	0.012***
	(0.003)
50% Female	0.009***
	(0.002)
75% Female	0.005**
	(0.002)
Quartile of Wage in Ind/Occ	
1st Quartile (lowest)	0.007***
	(0.002)
2nd Quartile	0.014**
	(0.006)
3rd Quartile	0.001
	(0.006)
4th Quartile (highest)	0.005
	(0.008)
IQR of wages in Ind/Occ ($1,000)	
IQR = $0	0.006
	(0.004)
IQR = $25,000	0.007***
	(0.002)
IQR = $50,000	0.008***
	(0.002)
IQR = $75,000	0.009**
	(0.004)
IQR = $100,000	0.010
	(0.006)

Notes: Sample contains women who are full-time employed (35+ hours/week) ages 25 to 55 with non-missing data. N=136,926. Model controls include occupation, industry, usual hours worked per week, health insurance (Medicare, Medicaid, ESI), veteran status, race/ethnicity, marital status, age, birth cohort, family size, number of children, homeowner, citizen, education, firm size, ADL & work disability. Share of women in industry-occupation group and below median wage are constructed in the sample for every industry and occupation pair. We cluster by industry-occupation groups and removed all industry-occupation groups that have less than 100 women. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.1 Appendix

Table A1: Part 1: Estimated Coefficients from Wage Equations for Prime Age Workers by Gender, 2011-2019

VARIABLES	(1) Women	(2) Men	(3) Women (Entropy Weighted)
Age 30-39	0.0691***	0.0849***	0.0450**
	(0.00749)	(0.00679)	(0.0188)
Age 40-49	0.0918***	0.132***	0.0464
	(0.0104)	(0.00942)	(0.0386)
Age 50-55	0.106***	0.142***	0.0531
	(0.0128)	(0.0118)	(0.0433)
Born 1957-1966	-0.00156	0.00233	-0.0360
	(0.0293)	(0.0257)	(0.0450)
Born 1967-1976	-0.00355	-0.0126	-0.0475
	(0.0301)	(0.0265)	(0.0491)
Born 1977-1986	-0.0519*	-0.0449	-0.112*
	(0.0312)	(0.0276)	(0.0597)
Born 1987-1996	-0.0999***	-0.0657**	-0.165**
	(0.0330)	(0.0291)	(0.0642)
NH Black	-0.0568***	-0.129***	-0.0672***
	(0.00538)	(0.00591)	(0.0180)
Hispanic	-0.0642***	-0.0851***	-0.0829***
	(0.00561)	(0.00561)	(0.0194)
AAIPI	0.00522	-0.0299***	-0.0346*
	(0.00776)	(0.00693)	(0.0196)
Other Race	-0.0634***	-0.0681***	-0.0534
	(0.0138)	(0.0156)	(0.0345)
Married	0.0730***	0.162***	0.0703***
	(0.00413)	(0.00452)	(0.0153)
Number of own children in household	0.0413***	0.0655***	0.0384***
	(0.00289)	(0.00265)	(0.00734)
Family Size = 2	-0.0574***	-0.0700***	-0.0596***
	(0.00634)	(0.00594)	(0.0178)
Family Size = 3	-0.102***	-0.116***	-0.0957***
	(0.00753)	(0.00648)	(0.0252)
Family Size = 4	-0.124***	-0.141***	-0.0862***
	(0.00899)	(0.00748)	(0.0247)
Family Size = 5	-0.177***	-0.185***	-0.139***
	(0.0115)	(0.00948)	(0.0282)
Family Size = 6+	-0.245***	-0.263***	-0.206***
	(0.0133)	(0.0117)	(0.0314)
Homeowner	0.0973***	0.111***	0.100***
	(0.00414)	(0.00382)	(0.0133)
Citizen	0.0450***	0.0453***	0.0469***
	(0.00635)	(0.00550)	(0.0179)
Veteran	0.0221	0.00861	0.0906**
	(0.0136)	(0.00547)	(0.0360)
Education: HS	0.142***	0.123***	0.177***
	(0.00945)	(0.00715)	(0.0377)
Education: Some college	0.234***	0.201***	0.272***
	(0.00974)	(0.00756)	(0.0400)
Education: College Graduate	0.463***	0.387***	0.497***
	(0.0101)	(0.00815)	(0.0419)
Education: Advanced Degree	0.650***	0.540***	0.674***
	(0.0111)	(0.00914)	(0.0449)
Observations	172,392	221,923	172,392

Notes: All wages in 2019 US dollars. Models include year and state FEs.

Part 2: Estimated Coefficients from Wage Equations for Prime Age Workers by Gender, 2011-2019

VARIABLES	(1) Women	(2) Men	(3) Women (Entropy Weighted)
Usual hours worked per week (last yr)	0.0120***	0.0113***	0.00867***
	(0.000329)	(0.000225)	(0.00126)
Medium firm	0.0658***	0.0765***	0.0850***
	(0.00521)	(0.00448)	(0.0149)
Large firm	0.113***	0.118***	0.146***
	(0.00502)	(0.00441)	(0.0154)
Medicaid	-0.199***	-0.189***	-0.210***
	(0.00842)	(0.00803)	(0.0408)
Medicare	-0.134***	-0.171***	-0.266**
	(0.0471)	(0.0501)	(0.126)
Has ESI	0.209***	0.189***	0.221***
	(0.0131)	(0.00979)	(0.0262)
ESI Response Missing	0.00139	-0.0534***	-0.0333
	(0.0134)	(0.0102)	(0.0270)
Disability = 1	-0.0822***	-0.0872***	-0.0317
	(0.0137)	(0.0110)	(0.0547)
Work Disability = 1	-0.105***	-0.158***	-0.0977
	(0.0155)	(0.0182)	(0.0624)
Industry			
Mining/oil_gas_extraction	0.407***	0.437***	0.494***
	(0.0495)	(0.0281)	(0.111)
Construction	0.294***	0.264***	0.406***
	(0.0416)	(0.0258)	(0.0890)
Manufacturing	0.285***	0.264***	0.351***
	(0.0399)	(0.0251)	(0.0837)
Wholesale_retail_trade	0.184***	0.175***	0.269***
	(0.0399)	(0.0253)	(0.0842)
Trans/Utilities	0.316***	0.329***	0.459***
	(0.0407)	(0.0254)	(0.0885)
Information	0.283***	0.276***	0.346***
	(0.0413)	(0.0267)	(0.0904)
Financial Activities	0.286***	0.286***	0.359***
	(0.0399)	(0.0258)	(0.0843)
Prof/Business Services	0.265***	0.276***	0.347***
	(0.0399)	(0.0252)	(0.0851)
Educ Health Services	0.179***	0.133***	0.230***
	(0.0398)	(0.0256)	(0.0844)
Other Services	0.158***	0.109***	0.213**
	(0.0404)	(0.0266)	(0.0850)
Leisure and Hospitality	0.212***	0.188***	0.242**
	(0.0409)	(0.0264)	(0.0968)
Public Admin	0.252***	0.278***	0.327***
	(0.0400)	(0.0257)	(0.0894)
Observations	172,392	221,923	172,392

Notes: All wages in 2019 US dollars. Models include year and state FEs.

Part 3: Estimated Coefficients from Wage Equations for Prime Age Workers by Gender, 2011-2019

VARIABLES	(1) Women	(2) Men	(3) Women (Entropy Weighted)
Occupation			
Business and Financial Operations	-0.106***	-0.0955***	-0.105***
	(0.00908)	(0.00859)	(0.0127)
Computer and Mathematical	0.0365***	0.0194**	0.0370**
	(0.0115)	(0.00787)	(0.0164)
Architecture and engineering	0.0307*	-0.0142*	0.0222
	(0.0161)	(0.00761)	(0.0203)
Life, physical, and social science	-0.155***	-0.198***	-0.125***
	(0.0239)	(0.0145)	(0.0281)
Community and social service	-0.332***	-0.448***	-0.330***
	(0.0105)	(0.0158)	(0.0238)
Legal	-0.00974	-0.0139	0.00899
	(0.0144)	(0.0170)	(0.0234)
Educ, training and library	-0.377***	-0.333***	-0.362***
	(0.00741)	(0.0101)	(0.0122)
Arts, design, enter, sports and media	-0.193***	-0.204***	-0.162***
	(0.0184)	(0.0145)	(0.0212)
Health care practitioners and technical	0.00778	-0.0240**	-0.0169
	(0.00771)	(0.0114)	(0.0151)
Healthcare support	-0.367***	-0.361***	-0.344***
	(0.00987)	(0.0205)	(0.0178)
Protective Services	-0.155***	-0.215***	-0.165***
	(0.0160)	(0.0102)	(0.0360)
Food prep and serving	-0.491***	-0.423***	-0.441***
	(0.0118)	(0.0134)	(0.0182)
Buildings and Grounds	-0.547***	-0.494***	-0.513***
	(0.0117)	(0.0102)	(0.0213)
Personal care and service	-0.486***	-0.382***	-0.415***
	(0.0129)	(0.0179)	(0.0350)
Sales and Related	-0.263***	-0.172***	-0.243***
	(0.00911)	(0.00815)	(0.0142)
Office and admin support	-0.303***	-0.363***	-0.308***
	(0.00626)	(0.00782)	(0.0121)
Farming, fishing, forestry	-0.405***	-0.287***	-0.297***
	(0.0360)	(0.0266)	(0.0744)
Construction and Extraction	-0.269***	-0.248***	-0.231***
	(0.0358)	(0.00880)	(0.0460)
Installation maintenance and repair	-0.197***	-0.213***	-0.157***
	(0.0308)	(0.00748)	(0.0460)
Production	-0.457***	-0.322***	-0.437***
	(0.0123)	(0.00746)	(0.0184)
Transportation and material moving	-0.474***	-0.381***	-0.472***
	(0.0140)	(0.00767)	(0.0250)
Observations	172,392	221,923	172,392

Notes: All wages in 2019 US dollars. Models include year and state FEs.

Table A2: Balancing Table

	Target Value	Unbalanced Value	Unbalanced Std. Dif.	Balanced Value	Balanced Std. Dif.
Age					
Age 30 to 39	0.326	0.307	-0.042	0.326	0.000
Age 40 to 49	0.325	0.327	0.005	0.325	0.000
Age 50 to 55	0.189	0.208	0.046	0.189	0.000
Birth Cohort					
Born 1957-1966	0.224	0.243	0.045	0.224	0.000
Born 1967-1976	0.321	0.319	-0.003	0.321	0.000
Born 1977-1986	0.323	0.308	-0.033	0.323	0.000
Born 1987-1996	0.130	0.127	-0.010	0.130	0.000
Race/Ethnicity					
Non-Hispanic Black	0.105	0.141	0.103	0.105	0.000
Hispanic	0.166	0.150	-0.043	0.166	0.000
AAPI	0.085	0.073	-0.046	0.085	0.000
Other/Multiple Race	0.011	0.013	0.016	0.011	0.000
Education					
HS Diploma	0.258	0.226	-0.078	0.258	0.000
Some College	0.253	0.296	0.093	0.253	0.000
College Degree	0.277	0.276	-0.004	0.277	0.000
Advanced Degree	0.156	0.167	0.030	0.156	0.000
Employer Sponsored Health Insurance	0.595	0.570	-0.049	0.595	0.000
ESI Status Missing	0.251	0.288	0.083	0.251	0.000
Medicaid	0.052	0.057	0.023	0.052	0.000
Medicare	0.002	0.002	0.000	0.002	0.000
Veteran	0.081	0.015	-0.544	0.081	0.000
Citizen	0.800	0.842	0.115	0.800	0.000
Married	0.625	0.573	-0.104	0.625	0.000
Number of Children	1.046	1.062	0.014	1.046	0.000
Homeowner	0.663	0.672	0.019	0.663	0.000
Usual Weekly Work Hours	44.543	42.098	-0.379	44.543	0.000

Notes: This table presents the balancing results and compares the distribution of various demographic and socioeconomic characteristics before and after entropy balancing to match a target distribution. Target Value column shows the target mean values for each characteristic. Unbalanced Value: These columns show the mean values and standardized differences (Std. Dif.) for each characteristic before balancing. Balanced Value: These columns show the mean values and standardized differences (Std. Dif.) for each characteristic after balancing. As in Table 1 balancing for ADL/presence of a disability, family size, firm size, industry, and occupation categories are not shown.