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Exploring how Determinants of the Gender Wage Gap in the United States have Changed Women's Wages over time, Highlighting Changes During the COVID-19 Period

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Abstract

Using IPUMS Current Population Survey (CPS) and CPS Annual Social and Economic Supplement (ASEC) microdata, new empirical evidence is presented on the changing levels and trends in the gender wage gap from 2009 to 2022, including a COVID-19 specific analysis. Based on the empirical research study performed in this paper, three main conclusions can be identified. First, when controlling for standard wage explanatory variables, the gender wage gap reduced during COVID-19, as women increased their wages by 3.12% relative to men. This is opposed to predictions from Alon et al. (2020) who projected the wage premium for men would rise during COVID-19. Second, we find that the gender wage gap is primarily driven by marital status, followed closely by child status. Married women have the largest wage gap out of the tested factors, with single women having 19% higher wages when controlling for married women, and childless women having 15% higher wages when controlling for women with children of any age. Finally, we see that the growth in the gender wage gap during COVID-19 was primarily caused by child status compared to marital status, as the wage gap fell more for women with no children than for single women. Future research will be proposed for expansions of the empirical study in this paper.

Keywords: Current Population Survey, Annual Social and Economic Supplement, gender wage gap, wage premium, COVID-19, marital status, child status

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I. Introduction

The gender wage gap in the United States has undergone significant research and investigation over the past century. From the 1950s to the 1970s, women consistently earned 60% of men's wages. EPI (2016) determined that in the 1980s, women began to earn significantly more, reducing the gap by over 10% in just ten years. Blau and Khan (2017) found that women earned about 79% of men on an annual basis. The U.S. Census Bureau (2022) found that women were "paid 77 cents for every dollar paid to a man - adding up to a difference of $11,782 over the course of the year". We see that this wage gap is highest in the states of Utah, where women earn 60 cents for every dollar paid to men, and in Wyoming 59 cents for every male dollar. This gap does not reverse when looking at subsects of the United States; The U.S. Census Bureau (2021) finds that in 435 congressional districts and the District of Columbia, women make less than men. These numbers show the consequences of systemic issues like sexism and white supremacy in the United States, showing how the country discriminates against women and their labor.

Typical wage gap studies, like Langdon and Klomegah's (2013), use standard human capital variables such as education, experience, occupation, age, race, and marital status to explain changes in wage gap levels over time. A variety of additional factors such as workplace harassment, job segregation, racial discrimination, and a lack of workplace childcare support policies have further driven the wage gap. This paper will look to analyze the various determinants of the gender wage gap over a 14-year time period to add additional commentary and analysis on the changing levels of women's wages. COVID-19's impact on the wage premium will also be studied to analyze recent changes in women's wages.

The first case of COVID-19 in the United States appeared on January 13, 2020, and less than a month later, President Trump declared a national public health emergency. With over 99 million coronavirus cases recorded in the United States, amounting to over one million deaths, COVID-19 diffused rapidly and impacted individuals politically, socially, and economically. A recession that is still present, and extreme health mandates forced people to adapt or take massive hits to their well-being (fiscally and otherwise). The labor market suffered due to nationwide business closures and layoffs ravaging companies across the board. Unemployment rates rose during the beginning of the pandemic and almost reached record highs, impacting leisure and hospitality services the most. COVID-19 caused the unemployment rate to rise to 13% in just five months. Workers in low-wage jobs were impacted the most in terms of their labor force participation rates. Kochhar and Bennett (2021) found that "from February 2020 to February 2021, employment among low-wage workers fell by 11.7%, from 28.1 million to 24.8 million." It is undeniable that the arrival of the coronavirus significantly impacted the U.S. labor market, and this effect can be even further broken down when analyzing its impact on men versus women.

Kochhar and Bennett (2021) found that in the first year of the pandemic, women had lower labor force participation rates and higher unemployment rates than men. Although the U.S. economy and labor market have slowly begun to recover from the detrimental effects of the pandemic, due to loosening health restrictions and an economical rebound, it is still true that men earn more than females. Rosalsky (2020) indicated that COVID-19 did not help to shrink the wage gap. Additionally, Alon et al. (2020) predicted that the gender wage gap would rise by five percent, "that the average female worker will earn about 76 cents for every dollar the average male worker makes." Alon et al. (2020) projects a 10 year turn around period for the gender wage gap to reverse the changes from COVID-19. This is partly due to COVID-19 causing the service sector to implode causing many women to leave their jobs to take care of their children.

This paper will empirically argue that the gender wage gap was lowered in the years immediately following the arrival of COVID-19. Based on the results from the empirical research study performed in this paper, when controlling for standard wage explanatory variables, the gender wage gap was reduced by 3.12% during COVID-19 (Chatterjee, 2022). We also find that the wage premium for men is primarily driven by marital status, followed closely by child status. Married women have the largest wage gap out of the tested factors, with single women having 19% higher wages when controlling for married women, and childless women having 15% higher wages when controlling for women with children of any age. Finally, we see that the growth in the gender wage gap during COVID-19 was primarily caused by child status compared to marital status, as the wage gap fell more for women with no children than for single females. It is critical to examine the determinants behind the gender wage gap in the United States to examine wage level changes over time. This allows for a critical examination of why the coronavirus pandemic has caused a change in the level of pay discrepancy. Prior to COVID-19, there were some gains made in the pay gap, so it is especially important to see how the arrival of an infectious disease impacted the labor market.

This research paper will look into the various factors, including marital and child status, poverty, and race, that play into the gender wage gap pre and post-COVID-19 pandemic. After providing an overarching literature review into the gender wage gap and its determinants to create context, a comprehensive empirical research study will be explained using various multiple linear regressions to determine what has impacted women's wages the most strongly. This study will help to answer the overall research question: how has the gender wage gap changed over time, highlighting changes during the COVID-19 pandemic? Potential applications and further research will be proposed to further examine the effect of various determinants on women's wages relative to men. This paper will conclude with the limitations of the study and the main takeawys from the results.

II. Literature Review

Many empirical studies about the gender wage gap have been conducted using a wide variety of explanatory variables to help explain changes in the wage gap level over time. Economists have developed foundational knowledge from the plethora of wage regression models that help to answer the question of why women in the United States earn less than men, and how has this trend evolved over the years. One such study from Blau and Khan (2006) used data from the Michigan Panel Study of Income (PSID), a major database that details workers' actual labor market experience, and found that the gender pay gap narrowed during the 1980s, slowed in the 1990s and increased once again in the 2000s. Blau and Winkler (2022) found several factors playing a role in the slowing of the gender pay convergence, including labor force participation rates dropping for women and workplace discrimination rates improving at a slow rate.

Blau and Khan (1997) also found out that an important factor in the continuation of women's wage inequality was the increase in the price of experience, which can be understood as returns to experience for women. Experience, a key human capital variable, was shown to have a negative impact on women over men. A 1991 decomposition model from Juhn, Murphy, and Pierce (1993) was used to determine how gender-specific factors such as qualifications, discrimination, and the effect of price changes common to both men and women affected the wage gap. This regression model used PSID data with hourly wage differences to test how human capital variables such as education, race, and experience, along with industry-specific factors, played into changing wage levels. Blau and Khan's research study (1997) concluded with three main factors that played into the slowing of the wage gap convergence: unmeasured gender characteristics narrowed at a faster pace in the 1980s compared to the 1990s, discrimination in the labor market occurred more frequently in the 1980s compared to the 1990s, and the demand and supply conditions for women were more favorable during the 1980s compared to the 1990s. These analyses show that there was an increase in female labor force participation in the 1980s, contributing to lower wages, and experience levels for women. According Friedberg (2003), technology, and computer workplace prevalence rose more rapidly in the 1980s than in the 1990s, helping women's wages during the 1980s more than men. These analyses are especially pertinent to this paper's research study as it was predicted that wages for women would decrease due to a similar trend of women's labor force participation rate declining during COVID-19.

Blau and Khan's research (2017) on the gender wage gap was expanded with updated PSID data from 1980 to 2010 and analyses related to the impact that additional explanatory variables had on wages. The updated study looked at men and women aged 25-64 who were full-time wage and salary workers who worked at least 26 weeks during the preceding year. This group of the labor market accounted for men and women with similar labor force commitment levels. Women had shorter work hours and more workforce interruptions when looking at higher-skilled occupations (higher-income), significantly contributing to the wage gap. Women at the top of the labor market, by income, saw a larger wage discrepancy compared to lower-earning women. This indicates that there is a ceiling in higher-paying, skilled jobs where women have higher barriers to entry than men.

On the other hand, it was found that women made gains in labor market experience and education. Blau and Khan (2017) found that women had higher levels of education and a significantly reduced differential in labor market experience in recent years. The experience of women was found to have positively changed from -7 years of experience in 1981 to -1.4 years of experience in 2011. Blau and Khan (2017) found that "gender differences in experience explained 24% of the gender gap in 1980 compared to 16% of the (considerably smaller) gender gap in 2010." Hirsch (2005) found that women in the labor market had higher rates of working part-time compared to full-time jobs, which led to lower hourly earnings for women compared to men. The updated research study denoted the log of wages for men and women as the dependent variables and explanatory factors education, experience, labor force participation, etc. as the independent variables. A regression model similar to Blau and Khan's research study will be employed in this research paper to analyze factors from 2009 to 2022 that have most significantly contributed to a change in gender wage gap levels. The overarching finding from this updated study was that typical human capital variables such as education, experience, and age did not explain much of the wage gap, but rather gender differences within industries and occupations maintained their relevance in explaining trends in the pay differential. Blau and Khan's study (2017) found that human capital factors were accounted for 27% of the gender wage gap in 1980, compared to only 8% in 2010. Selection bias was found to yield inconclusive and opposing results, revealing that further research is needed to fully understand its effect as a factor of the wage gap.

Further research from the Federal Reserve Bank of St. Louis (2020) related to marital status and its relation to the gender wage gap reveals that married men's elevated wages account for a large portion of the gender wage gap in the U.S. Data from the IPUMS database shows that married Black and white males had the highest overall wages. It was discovered that married white men did work the longest hours, but the difference was not significant compared to other groups. Additional data from Perry (2021) show that marriage and motherhood have a significantly negative effect on women's earnings. Perry concludes that the lower earnings for women may not be from labor market discrimination, but could likely be attributed to personal family and work choices. The child status of an individual was also significantly linked to lower wages in a research study performed in Denmark, a country with a wage gap similar in level to the U.S. Kleven et al. (2019) found that in Denmark, women with no children have similar wages to men, and mothers have significantly lower wages than men. They also find that women experience a sharp decline in their wages after the birth of their first child. No similar trend was observed for men. This shows the importance of marital status and child status as a determinant of the wage gap, important factors that will be analyzed and discussed in more detail later in this paper.

A more updated look at the gender wage gap from Collins (2020) that mothers with young children have experienced shortening work hours at a rate five times higher than their husbands. This caused the gender gap in work hours to increase from 20 to 50 percent. Data from the CPS from February through April 2020 was used to determine that the traditional household patterns of gender inequality are widening. Mothers have been taking on a larger burden of childcare and homeschooling which causes their overall work hours to decrease. While this can be seen across multiple age groups, this phenomenon is especially prevalent in families with primary and young children. This research is especially relevant to the COVID-19 time period highlighted within this paper. Kalenkoski (2022) details the differential effects, by marital status and gender, that favor married men over married women. The evidence in the paper suggests that self-employed married mothers were forced out of the labor force to care for children due to gender norms and the traditional notions of labor within households. This supports Collins et al.'s assertions, and further shows that COVID-19 has disproportionately impacted women compared to men. This research study will attempt to analyze the determinants of the gender wage gap from 2009 to 2022 in order to determine what factors have significant positive and negative returns to the labor market.

III. Empirical Analysis

Data

The data in this research paper comes from the database called Integrated Public Use Microdata Series (IPUMS), a highly accredited archive that has provided census and survey data around the world since 1962 (Ruggles, et al., 2022). The IPUMS Current Population Survey (CPS) is used to get demographic, educational, labor force status, and family data for the U.S. population. According to the I.P.U.M.S. Team (2022), the CPS is administered monthly by the U.S. Bureau of the Census to over 65,000 households. IPUMS CPS data is considered microdata as it provides information about individual people and households. Additional U.S Census Bureau data (2021) from the CPS Annual Social and Economics (ASEC) Survey was used to get income, earnings, and poverty data. The ASEC is a supplemental CPS survey that is conducted every year in the month of March. Thus, because wage data is essential to answering the research question, the data in this paper is limited to microdata within the month of March. For this reason, the COVID-19 period considered for analyses had to be adjusted. Because COVID-19 entered the U.S. in January 2020, hourly and yearly salary wage data would not have been impacted as early as March 2020. Thus, in this research study, the years 2021 and 2022 are considered to be the COVID-19 period.

2009 to 2022 was chosen as the time period for this research study to incorporate 12 years before COVID-19 as a comprehensive time series analysis to compare the effects of various determinants of the wage gap on changing wage levels. The overall data set was filtered to include only working-aged people, consisting of ages 18 to 64.

Furthermore, wages were adjusted for inflation using yearly CPI data. 2022 was used as the base year for the inflation adjustment to provide the most up-to-date look at wages. In total, the data set includes 1,090,039 individuals within the U.S., including 566,496 males and 523,543 females.

The independent variables used in this research study are *race* (if an individual is Black or not), *child status* (segmented by all children and children less than five years old), *poverty status*, and *marital status*. From the IPUMS database, the independent variables are shown as RACE, NCHILD / NCHILT5, OFFPOV, and MARST (U.S. Census Bureau, 2021). The dependent variable is *log(Wages)*. From the IPUMS database, wages are shown as INCWAGE. Wages are a yearly salary number for each person. Hourly wages were also calculated and summary statistics related to hourly wages are included in the descriptive statistics section. Regression results for yearly salary wages and hourly wages were the exact same, so yearly salary wage data was chosen as the metric of analysis. The log of wages was taken to normalize the wage data so it could be accurately used in a regression model. Income and earnings data is typically right-skewed as people who make disproportionately large wages pull the mean much higher than the median, making the residuals not normal. Additionally, income and earnings data usually consist of extremely high values which need to be normalized to perform a regression analysis. Thus, to descale the effect of the large wage values, the log of wages is taken. Taking the log of income wages shows the increase or decrease in wages as changing proportionally rather than linearly. This allows for the change in wages over time to be measured by percent change rather than by a dollar amount.

Descriptive Statistics

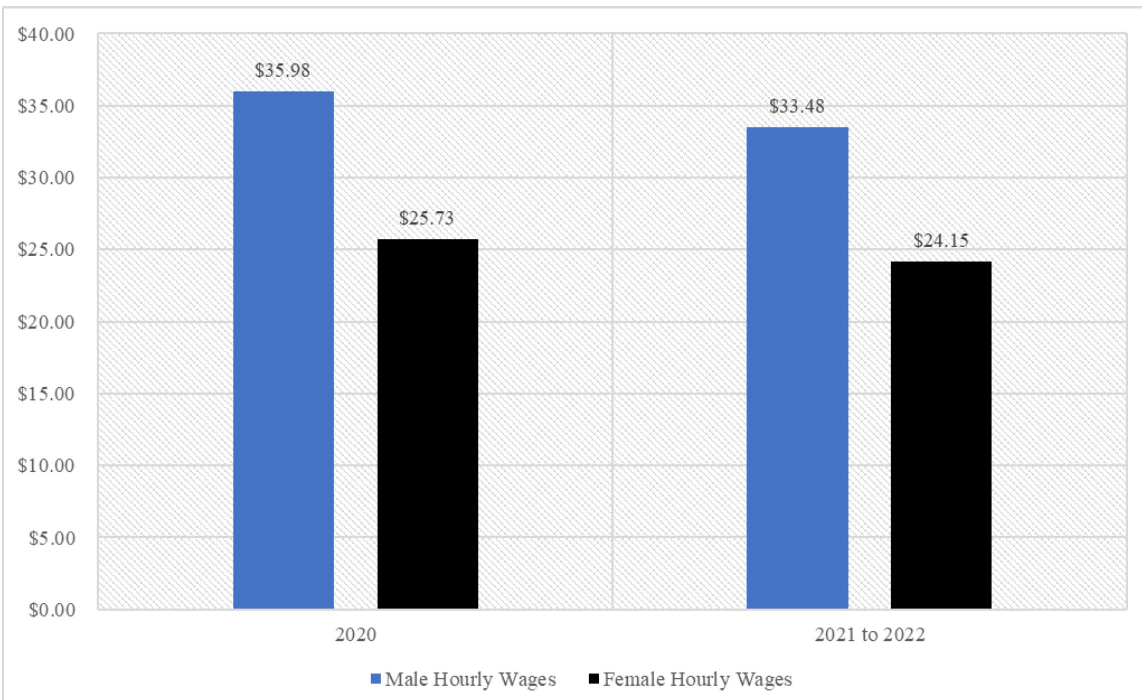
From preliminary data analyses, a number of interesting metrics were found that help to explain year-over-year trends and changes to wages:

Figure 1 segments hourly wage data prior to and during COVID-19 to analyze how wages have changed for men and women during the coronavirus recessionary period. We can see that wages from 2020, the year before COVID-19 arrived in the U.S. as defined by our data specifications, are 28.49% higher for men compared to women. From 2021 to 2022, during COVID-19, wages were only 27.87% higher for men. This means that prior to the COVID-19 pandemic, women earned $0.71 to a man's $1. During COVID-19, women earned $0.72 to a man's $1. This small decrease in the gender wage gap does not control for any explanatory variables such as *education*, *experience*, *marital status*, *child status*, *poverty*, or *race*.

Alon et al. (2020) noted that women were predicted to earn $0.76 to a man's dollar due to COVID-19. The small discrepancy in the gender wage gap value is due to the particular sample that the IPUMS CPS survey measures. While more comprehensive research studies focused on the gender wage gap may arrive at a different number due to a larger sample size (greater than the 1,090,039 individuals within this research study), the overall trends found within this research study still hold true. This is because the IPUMS CPS database consists of survey data that is considered to be representative of the entire U.S. population. Thus, while certain values presented in this research study may differ from other research studies that include more data points, the analyses presented in this paper still shed light on the factors that have impacted the gender wage gap.

On average, women have slightly higher education levels than men. Men had an average education level of 13.81 which corresponds to an approximate education level between “some college but no degree” and a “two years of college”. Women’s average education level was 14.21 which corresponds to an approximate educational level of “associate's degree, occupational/ vocational program”.

Figure 1: Comparing Male vs. Female Hourly Wages from 2020 to 2021-2022



Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author’s calculation

Men and women had almost identical experience levels. Experience, a constructed variable with the formula age minus years of schooling, had a mean value of 26.78 for men and 26.45 for women. Within the male data set, 11.48% of individuals were Black (racial metric). 15.56% of the female data set was Black.

Empirical Model

Three different types of multiple linear regressions were used to determine the effects that various determinants of the gender wage gap have had on female wages over the time period from 2009 to 2022.

Model I: Baseline Female Wage Gap Regression Model

$$\begin{aligned}\log(Wage)_{(i,t)} &= \beta_1 + \beta_2 Is\_Year_{(t)} + \beta_3 Is\_Female\_Year_{(i,t)} \\ &+ \beta_4 Education_{(i,t)} + \beta_5 Experience_{(i,t)} + \beta_6 Experience^2{}_{(i,t)} \\ &+ \beta_7 Is\_Black_{(i,t)} + \varepsilon_{(i,t)}\end{aligned} \quad \textbf{(1)}$$

Due to the popular nature of research on the gender wage gap, many well-established models have been created to explain the effects that different variables have on wages. One of the most widely used models in empirical economics relating to wage gap research is the Mincer earnings function, which explains wage income as a function of schooling and experience (Polacheck, 2008). Widely accepted as the standard model for wage regressions, this research study employs Mincer's model as a baseline female wage gap model, using *education*, *experience*, and *race*. The *experience* variable was constructed using the formula age minus years of schooling. *Race*, which is represented by the dummy variable *Is_Black*, has also been noted in many research studies as a core piece of a wage gap regression. Model I is used to establish a baseline wage gap for women when controlling for time (*Is_Year*), *education*, *experience*, and *race*. The variable *Is_Female_Year* is a dummy variable that accounts for a female individual's data values for a particular year. For example, if an individual is a female and is found within the year 2009, their *Is_Female_Year* value would be 1. That same individual would have a value of 0 for the *Is_Female_Year* variables from 2010 to 2022. By making the *Is_Female* variable time-variant, we can measure each year's individual wage gap from a woman's perspective. β_3 represents the wage gap from a woman's perspective. Because income is measured as the log of wages, the β_3 can be interpreted as

$$\beta_3 = \frac{\%\Delta Wage}{\Delta Is\ Female\ Year},$$

or the return to females by year in the labor market. Substituting another independent variable such as *marriage* for *Is_Female_Year* (β_4) would determine the return to marriage in the labor market.

Model II: Baseline Model Controlling for Time-Variant Independent Variables

$$\begin{aligned}\log\,(Wage)_{(i,t)} &\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \textbf{(2)}\\ &= \beta_1 + \beta_2 Is\_Year_{(t)} + \beta_3 Is\_Female\_Year_{(i,t)}\\ &+ \beta_4 Is\_Independent.Variable\_Year_{(i,t)} + \beta_5 Education_{(i,t)}\\ &+ \beta_6 Experience_{(i,t)} + \beta_7 Experience^2{}_{(i,t)} + \beta_8 Is\_Black_{(i,t)}\\ &+ \varepsilon_{(i,t)}\end{aligned}$$

Due to the categorical nature of the data, i.e. metrics on gender, marital status, child status, poverty status, and race, many additional dummy variables were created to make different independent variables time-variant. Time-variant variables, e.g. β_2, β_3, and β_4, will have fourteen associated coefficient values, each representing a year from 2009 to 2022. By making variables such as gender, marital status, child status, poverty status, and race status time-variant, changes to *log(Wages)* can be measured over time to determine each year's individual effect on wages. Furthermore, when controlling for time-variant independent variables (which account for the effect of each respective variable on *wages*) we can analyze how a single variable, such as marriage, has impacted wages over time. For example, when including *Is_Education_2009…2022*, we can measure how overall female wages have changed over time when controlling for both male and female education. Plotting the β_3 coefficients against the baseline wage gap model by year allows for an examination of how controlling for different independent variables has an impact on the gender wage gap trend. This process is the same for each independent variable, allowing for a detailed examination of many determinants of the gender wage gap over time. Model II is used to measure how the gender wage gap changes when controlling for a shared (men and women) time-variant independent variable. An important nuance to note is that when using the time-variant version of race in Model II, the standard control for this variable, found in Model II as β_8*Is_Black*, is omitted in the regression. This holds true for Model III as well.

Model III: Baseline Model Controlling for Time-Variant-Female Independent Variables

$$\begin{aligned}\log(Wage)_{(i,t)} &= \beta_1 + \beta_2 Is\_Year_{(t)} + \beta_3 Is\_Female\_Year_{(i,t)} \\ &+ \beta_4 Is\_Independent.Variable\_Year_{(i,t)} \\ &+ \beta_5 Is\_Independent.Variable\_Female\_Year_{(i,t)} \\ &+ \beta_6 Education_{(i,t)} + \beta_7 Experience_{(i,t)} \\ &+ \beta_8 Experience^2{}_{(i,t)} + \beta_9 Is\_Black_{(i,t)} + \varepsilon_{(i,t)}\end{aligned} \tag{3}$$

Model III is the most important model within this research study as it provides the most relevant analyses relating to the specific effects that different determinants of the gender wage gap have had on changing wage gap levels over the years. Model III controls for the same factors as Model I and II, but by making time-variant independent variables (seen in Model II) gender-specific, we are able to examine how various independent variables, when directly linked to the female gender, impact female wages specifically. Model III provides two useful analysis metrics: β_3 and β_5.

These coefficient values are better understood through an example from the performed regressions, corresponding to Tables A8 and A9:

$$\begin{aligned}\log\,(Wage)_{(i,t)} &= \beta_1 + \beta_2 Is\_2009\ldots2022_{(t)} \\ &+ \beta_3 Is\_Female\_2009\ldots2022_{(i,t)} \\ &+ \beta_4 Is\_Marriage\_2009\ldots2022_{(i,t)} \\ &+ \beta_5 Is\_Marriage\_Female\_2009\ldots2022_{(i,t)} \\ &+ \beta_6 Education_{(i,t)} + \beta_7 Experience_{(i,t)} \\ &+ \beta_8 Experience^2{}_{(i,t)} + \beta_9 Is\_Black_{(i,t)} + \varepsilon_{(i,t)}\end{aligned} \tag{3}$$

When including *Is_Marriage_Female*_2009…2022 into the regression model can track how overall female wages and married female wages have changed from 2009 to 2022 when controlling for time-variant female experience. β_3 represents the overall female wage gap, for females that are not married, for a particular year. Similar to Model II, there will be fourteen coefficient values for β_3, each showing the respective years' gender wage gap when controlling for the same factors in Model I, time-variant experience, and time-variant-female experience. β_5 represents the wage gap for *married females* for a particular year. Plotting β_3 and β_5 against the baseline wage gap model shows how both *single females* and *married females'* wages have changed in comparison to the baseline wage gap. This process is the same for each independent variable, allowing for a detailed examination of many determinants of the gender wage gap over time.

IV. Results

This research study performs many multiple linear regressions to analyze the effects that the independent variables *race*, *child status*, *poverty status*, and *marital status* have had on the gender wage gap from 2009 to 2022, highlighting recent changes during the COVID-19 pandemic. In order to accurately control for each of these variables during regressions, two separate regressions were required for each independent variable to control for the time-variant and time-variant-female versions of these variables. Each regression also accounts for the effects of time in the form of *Is_2009*, *Is_2010*, etc. found at the top of the regression tables. Further discussion on specific results will be discussed below. A breakdown of each of the three regression models performed in this research study is as follows:

From Model I, the baseline female wage gap, when accounting for the standard wage regression variables *education*, *experience*, and *experience*^{2}, is found by plotting the coefficients in front of the *Is_Female_2009, Is_Female_2010*, etc. variables by year. These values show a percent difference in male and female wages, from a female's perspective, which can be plotted in a graph (Figure 2) by year to visually see the change over time.

From Model II, the overall female wage gap, when controlling for a time-variant independent variable, is found by plotting the values in front of the *Is_Female_2009*, *Is_Female_2010*, etc. variables by year. These values are compared to the baseline female wage gap values in a combined graph to analyze changes in female wages over time when accounting for the effects of an independent variable on both males and females. As seen in Figure 3, the results from Model II indicate that controlling for the effects of a particular independent variable over time on both men and women does not have a strong effect in explaining changes in the gender wage gap. Thus, Model III is required to determine the causes of changes in the gender wage gap over time.

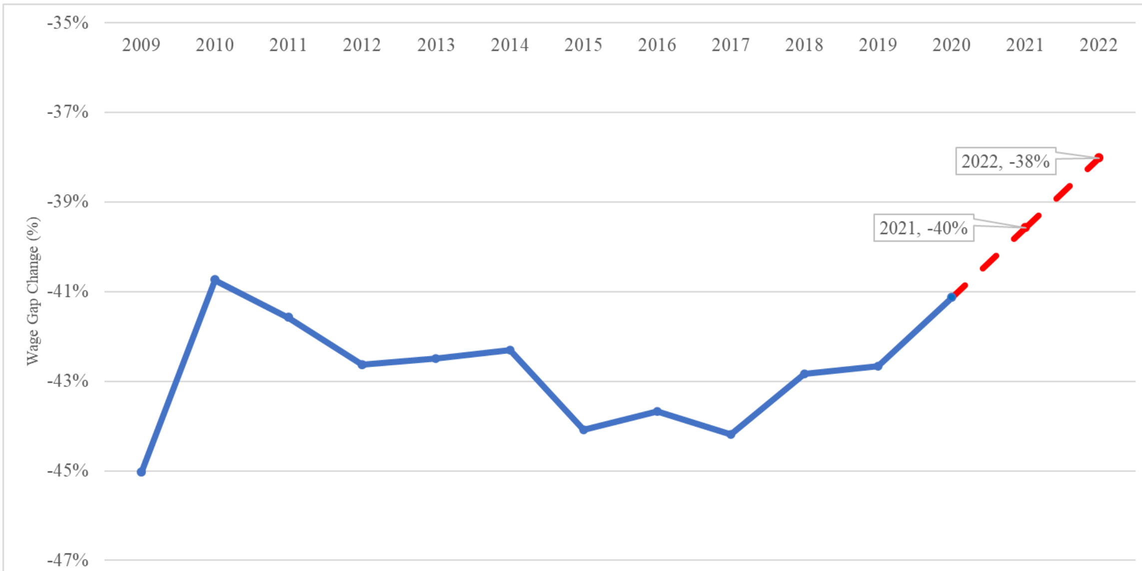
From Model III, the overall female wage gap, when accounting for the presence of a time-variant gender-specific independent variable, is found by plotting values in front of the *Is_Female_2009*, *Is_Female_2010*, etc. variables by year. These values are compared to the baseline female wage gap values in an individual and combined graph to analyze changes in overall female wages over time. This shows how, when accounting for the effects of an independent variable on females only, the gender wage gap changes. Furthermore, from the coefficient values in front of the time-variant-female variables (e.g. *Is_Married_Female_2009*), we can see how wages for a particular group of individuals (e.g. *Married Females*) have changed over time. Model III's analyses are the most pertinent in this research study.

Nine separate regressions were performed in this research study. For organizational and ease of reading purposes, not all regression results and graphs will be shown in the main section of this paper. The baseline female wage gap regression result and its respective graph are included, and graphs separating Models II and III into easier-to-read segments are shown. Regression results for has.child of all ages is shown in the main section of the paper; all other regression results are shown in the appendix.

Model I

Model I regression results are shown in Table 1 and Figure 2, seen below.

Figure 2: Baseline Female Wage Gap



Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

Table 1: Baseline Female Wage Gap

	Dependent variable:
	Log Wages
Is_2009	0.021*** (0.006)
Is_2010	−0.039*** (0.006)
Is_2011	−0.066*** (0.006)
Is_2012	−0.056*** (0.006)
Is_2013	−0.055*** (0.006)
Is_2014	−0.044*** (0.006)
Is_2015	−0.006 (0.006)
Is_2016	0.015** (0.007)
Is_2017	0.034*** (0.006)
Is_2018	0.033*** (0.007)
Is_2019	0.058*** (0.007)
Is_2020	0.070*** (0.007)
Is_2021	0.006 (0.007)
Is_2022	
Is_Female_2009	−0.450*** (0.006)
Is_Female_2010	−0.407*** (0.006)
Is_Female_2011	−0.416*** (0.006)
Is_Female_2012	−0.426*** (0.006)
Is_Female_2013	−0.425*** (0.006)
Is_Female_2014	−0.423*** (0.006)
Is_Female_2015	−0.441*** (0.006)
Is_Female_2016	−0.437*** (0.006)
Is_Female_2017	−0.442*** (0.006)
Is_Female_2018	−0.428*** (0.006)
Is_Female_2019	−0.427*** (0.006)
Is_Female_2020	−0.411*** (0.007)
Is_Female_2021	−0.396*** (0.007)
Is_Female_2022	−0.380*** (0.007)
Educ	0.153*** (0.0003)
Experience	0.090*** (0.0003)
Experience_Sqrd	−0.001*** (0.00001)
Is_Black	−0.134*** (0.003)
Constant	7.383*** (0.008)
Observations	1,090,039
R^2	0.284
Adjusted R^2	0.284
Residual Std. Error	0.870 (df = 1090007)
F Statistic	13,933.670*** (df = 31; 1090007)
Signficance Levels	*p<0.1; **p<0.05; ***p<0.01

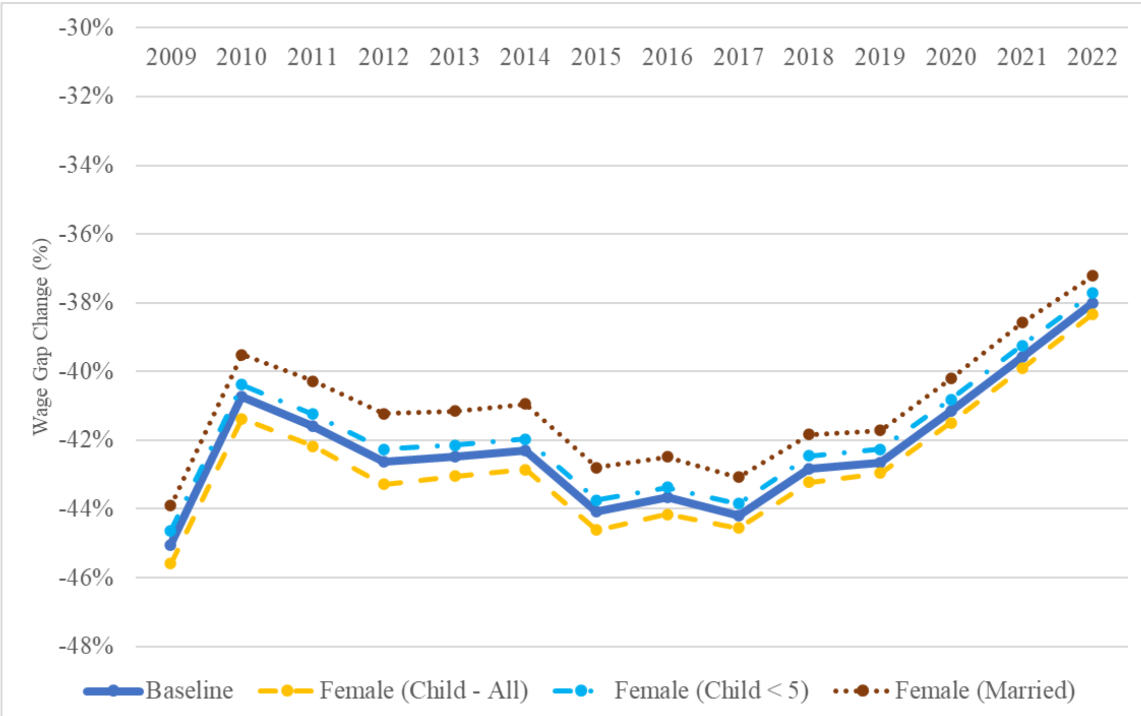
Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

As noted above, the baseline regression model is used to establish a "normal wage gap" level for comparison against the Model II and Three regressions. Plotting the coefficients in front of the *Is_Female_Year* dummy variables, which account for a female individual's data values for a particular year, over time yields Figure 2. From Table 1, we see that the variables are all statistically significant with p-values less than 0.01. Additionally, Model I has a relatively high R^2 value of 0.284, indicating that 28.4% of the variability observed in *log(Wages)* is explained by the regression model. The baseline regression model shows that when controlling for *education*, *experience*, *experience²*, and *race*, women in 2022, on average, make 38% less than a man, or $0.62 for every dollar a man makes. In the descriptive statistics section, it was noted that during COVID-19, women earned $0.72 to a man's $1, according to preliminary data analysis. This indicates that controlling for *education*, *experience*, *experience²*, and *race*, further lowers women's wages by $0.10. Figure 2 shows that the gender wage gap, in the aftermath of the 2007 recession, decreased (women's wages went up relative to men's), but slowly widened until 2016. COVID-19, as opposed to predictions from many economists, caused women's wages to rise relative to men's. When controlling for standard wage explanatory variables, the gender wage gap was reduced by 3.12% during COVID-19. Model II and III's regressions will help to further explain why women earned relatively more than men during the coronavirus pandemic.

Model II

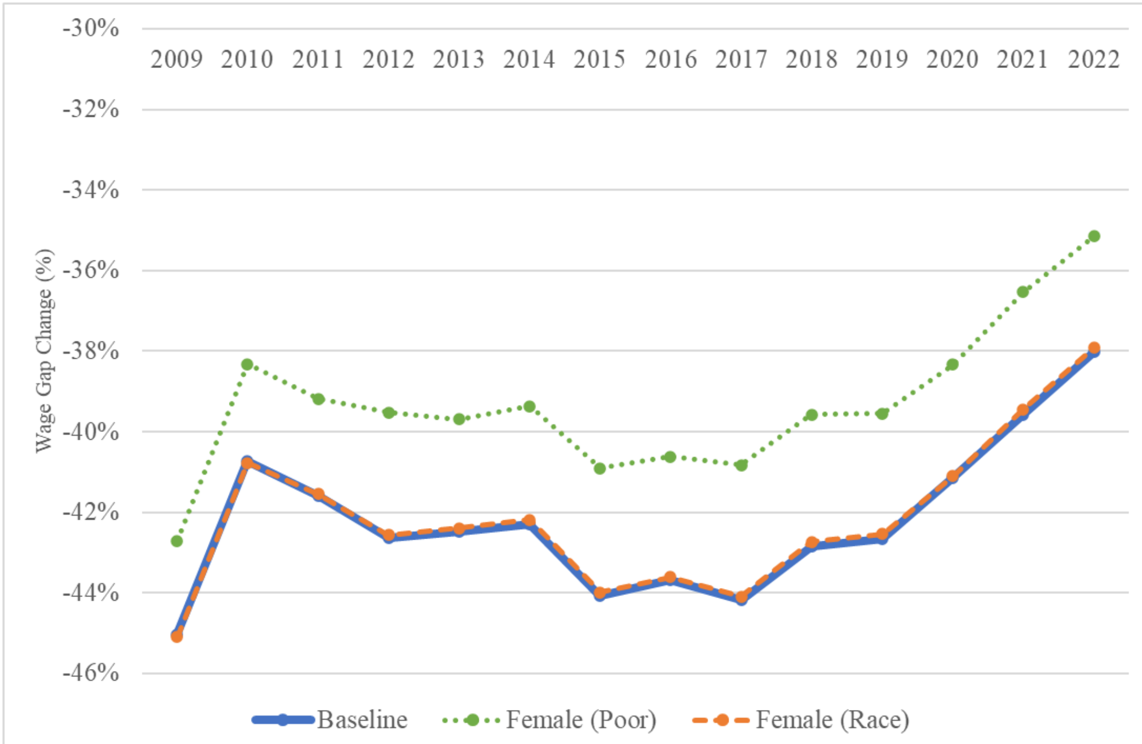
Model II and III's regression results have been combined into a single table for organizational purposes. Condensed and full versions of Model II's regression can be found in the main body and appendix. Model II's regression results, when plotted in Figures 3 and 4, do not reveal any major analyses besides overall wage gap level changes. From the plot, we see that, when making variables such as *marital status, child* *status, poverty status,* and *race* status time-variant, changes to *log(Wages)* can be measured over time to determine each year's individual effect on wages. The interpretation of the graph, taking *marriage* as an example, is as follows: when including *Is_Marriage_2009…2022*, we see a slight increase in overall female wages (one to two percent) when controlling for both male and female marriage. Controlling for male and female poverty levels has the most significant positive impact on overall female wages, with *poverty* increasing women's wages by approximately three percent. On the other hand, controlling for male and female children (all ages) has the most significant negative impact on overall female wages, with *children (all ages)* decreasing women's wages between zero and one percent. Controlling for *children (<5 years of age)* increases overall female wages slightly, but does not have a significant effect on the wage level. *Race* has no effect on the overall female wage level. These values are not high, indicating that just controlling for time-variant independent variables does not paint a comprehensive picture of the changing level of the gender wage gap. A gender-specific analysis of the independent variables is needed.

Figure 3: Female Wages: Controlling for Time-Variant Child (all ages), Child (<5 years), Marriage vs. Baseline Wage Gap



Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

Figure 4: Female Wages: Controlling for Time-Variant Poverty and Race vs. Baseline Wage Gap



Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

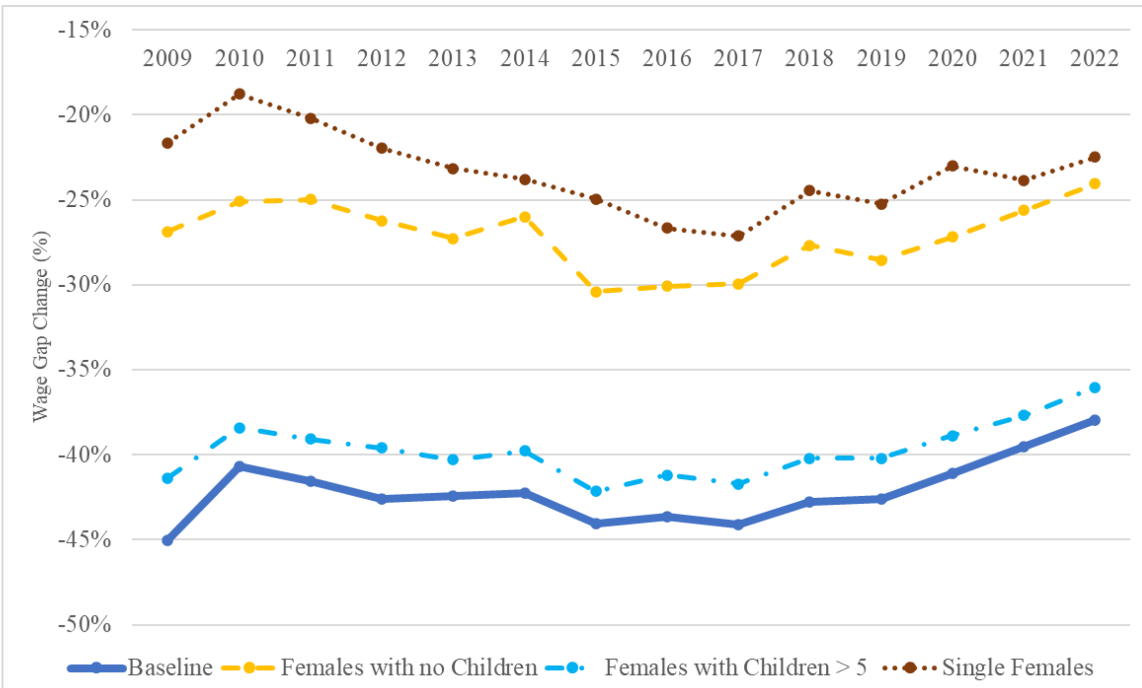
Model III

Model III's regression results will be separated into two sections: one detailing how overall female wages, when controlling for the gender-specific independent variable, changes, and the second detailing how the specific group of independent variable females' (i.e married females, poor females, etc.) wages have changed. All regression results and associated graphs, if not in the main section, are in the appendix section.

***Is_Female_2009…2022* coefficients by year against the baseline:**

Figures 5 and 6 shows the independent variables plotted against Model I's baseline to see changes that each variable has on overall female wages from 2009 to 2022. Each independent variable will be discussed separately below. All coefficients are statistically significant (refer to Tables) with p-values less than 0.01 and strong R^2 values.

Figure 5: Overall Female Wages: Females with no Children, Females with Children > 5 Years , Single Females vs. Baseline Wage Gap



Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

Females with No Children; Figure A1, Tables 2 and A1

Recall that the line shown in Figure 5 and A1 shows how the wages of females with no children (controlling for females with children of all ages) have changed over time. Figure A1 shows that the overall level of female wages is higher when controlling for time-variant females with children of any age by an average of 15%. This indicates that females with children of any age bring down overall female wages. This wage gap also matches the baseline model in trends from 2009 to 2022, as we see a clear increase in childless women's wages as COVID-19 began.

Table 2: Controlling for Has.Child_Female (all) vs. Baseline - Condensed

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_Female_2009	−0.457*** (0.006)	−0.269*** (0.009)
Is_Female_2010	−0.415*** (0.006)	−0.251*** (0.009)
Is_Female_2011	−0.423*** (0.006)	−0.250*** (0.009)
Is_Female_2012	−0.434*** (0.006)	−0.262*** (0.009)
Is_Female_2013	−0.431*** (0.006)	−0.273*** (0.009)
Is_Female_2014	−0.429*** (0.006)	−0.260*** (0.009)
Is_Female_2015	−0.447*** (0.006)	−0.304*** (0.009)
Is_Female_2016	−0.442*** (0.006)	−0.301*** (0.009)
Is_Female_2017	−0.446*** (0.006)	−0.299*** (0.009)
Is_Female_2018	−0.433*** (0.006)	−0.277*** (0.009)
Is_Female_2019	−0.430*** (0.006)	−0.286*** (0.009)
Is_Female_2020	−0.416*** (0.007)	−0.272*** (0.010)
Is_Female_2021	−0.400*** (0.007)	−0.256*** (0.010)
Is_Female_2022	−0.384*** (0.007)	−0.241*** (0.010)
Is_Child_Female_2009		−0.339*** (0.012)
Is_Child_Female_2010		−0.295*** (0.012)
Is_Child_Female_2011		−0.314*** (0.012)
Is_Child_Female_2012		−0.313*** (0.012)
Is_Child_Female_2013		−0.290*** (0.012)
Is_Child_Female_2014		−0.312*** (0.012)
Is_Child_Female_2015		−0.263*** (0.012)
Is_Child_Female_2016		−0.262*** (0.013)
Is_Child_Female_2017		−0.276*** (0.013)
Is_Child_Female_2018		−0.295*** (0.013)
Is_Child_Female_2019		−0.279*** (0.013)
Is_Child_Female_2020		−0.278*** (0.014)
Is_Child_Female_2021		−0.279*** (0.013)
Is_Child_Female_2022		−0.280*** (0.014)
Educ	0.153*** (0.0003)	0.152*** (0.0003)
Constant	7.441*** (0.008)	7.386*** (0.009)
Observations	1,090,039	1,090,039
R^2	0.286	0.291
Adjusted R^2	0.286	0.291
Residual Std. Error	0.869 (df = 1089993)	0.866 (df = 1089979)
F Statistic	9,705.790*** (df = 45; 1089993)	7,585.143*** (df = 59; 1089979)
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01

Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

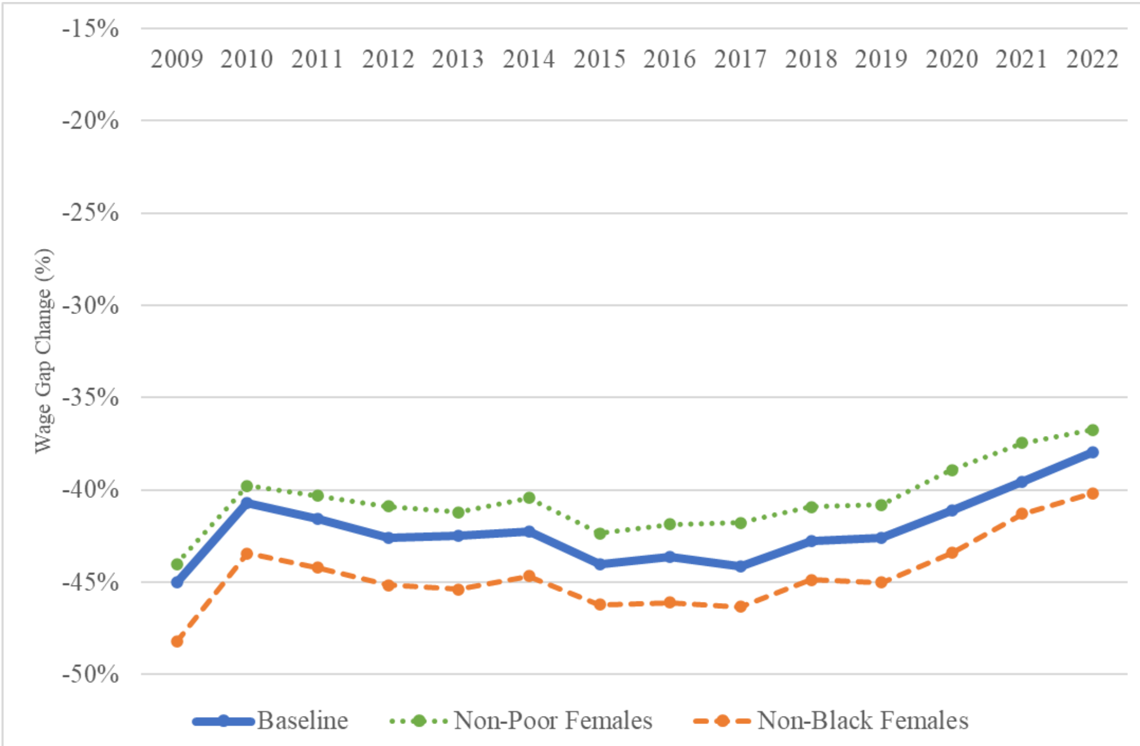
Females with Children > 5 Years; Figure A3, Tables A2 and A3

The line shown in Figure 5 and A3 shows how the wages of females with children over the age of five years (controlling for females with children less than five years) have changed over time. Figure A3 shows that when controlling for a time-variant female with a child under five years old, the overall level of female wages is higher by an average of two percent from 2009 to 2022. This shows that having a child negatively impacts female wages as this wage level change is much less than the change for wages of females with no children. This could be because children require an increased time commitment and child support, decreasing the amount of time that is allocated to work. The dynamics of the wage changes match the baseline model, as we see an increase in overall women's wages during COVID-19.

Single Females; Figure A9, Tables A8 and A9

The line shown in Figures 5 and A9 shows how the wages of single women (controlling for married females) have changed over time. Figure A9 shows that the overall level of female wages is significantly higher when controlling for time-variant married females by an average of 19%. This indicates that married females significantly bring down overall female wages; this means that married females experience the highest gender wage gap disparity among all the groups studied in this research paper (confirmed in the next section). Additionally, the dynamics of single women's wage gap changes differs from the baseline model, as wages steadily dropped from 2010 to 2017, and then slowly increased until 2022. We see no increase in single women's wages during the COVID-19 period.

Figure 6: Overall Female Wages: Non-Poor Females and Non-Black Females vs. Baseline Wage Gap



Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

Non-Poor Females; Figure A5, Tables A4 and A5

The line shown in Figures 6 and A5 shows how the wages of non-poor women (controlling for poor females) have changed over time. In this research study, non-poor women refer to any woman above the poverty line. Figure A5 shows that the overall level of non-poor female wages is higher when controlling for time-variant poor females by an average of two percent. This shows that when accounting for the effects of poor females, overall women's wages rise from 2009 to 2022. This further indicates that non-poor women have a slightly lower wage gap than poor women. The dynamics of the wage changes match the baseline model, as we see an increase in overall women's wages during COVID-19.

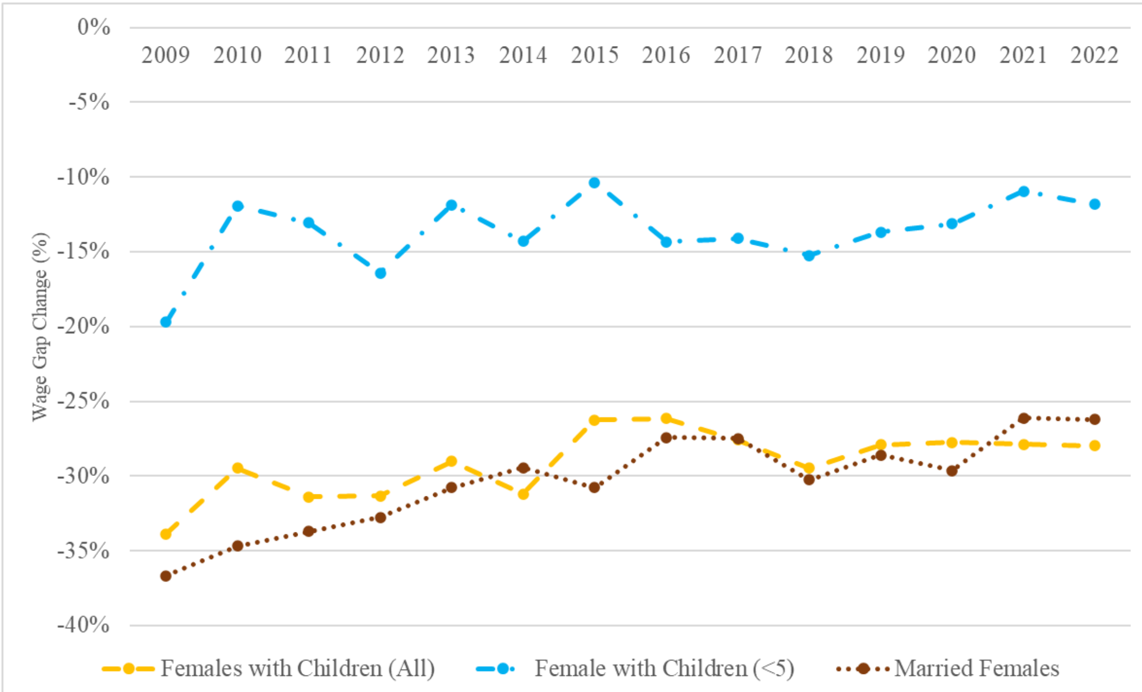
Non-Black Females; Figure A7, Tables A6 and A7

The line shown in Figures 6 and A7 shows how the wages of non-Black women (controlling for Black females) have changed over time. Figure A7 shows that the overall level of non-Black female wages is lower when controlling for time-variant Black females by an average of two percent. This indicates that the gender wage gap for women is worse when removing Black women, indicating that Black women help to raise women's wages. The dynamics of the wage changes match the baseline model, as we see an increase in overall non-black women's wages during COVID-19.

Is_Independent.Variable_Female_2009…2022 **coefficients by year against the baseline*:***

Figures 7 and 8 show the independent variables plotted against Model I's baseline for a comparison of the changes each gender-specific variable has on wages from 2009 to 2022. Each independent variable will be discussed separately below. All coefficients are statistically significant with p-values less than 0.01 and strong R^2 values.

Figure 7: Variable Specific Female Wages: Females with Children (All Ages), Females with Children (< 5 Years), Married Females



Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

Has Child (All Ages); Figure A2, Tables 2 and A1

Figures 7 and A2 shows that women with children of any age, compared to men with children of any age, experience approximately 30% lower wages. We also see that women with children of any age have increased their wages from 2009 to 2020 by approximately six percent. As COVID-19 began, this increase in wages plateaued, indicating that these women's wages were hurt when controlling for women with children. Because the overall value of this line lies in the negative, it indicates that women with children of any age experience decreasing wages compared to men with children.

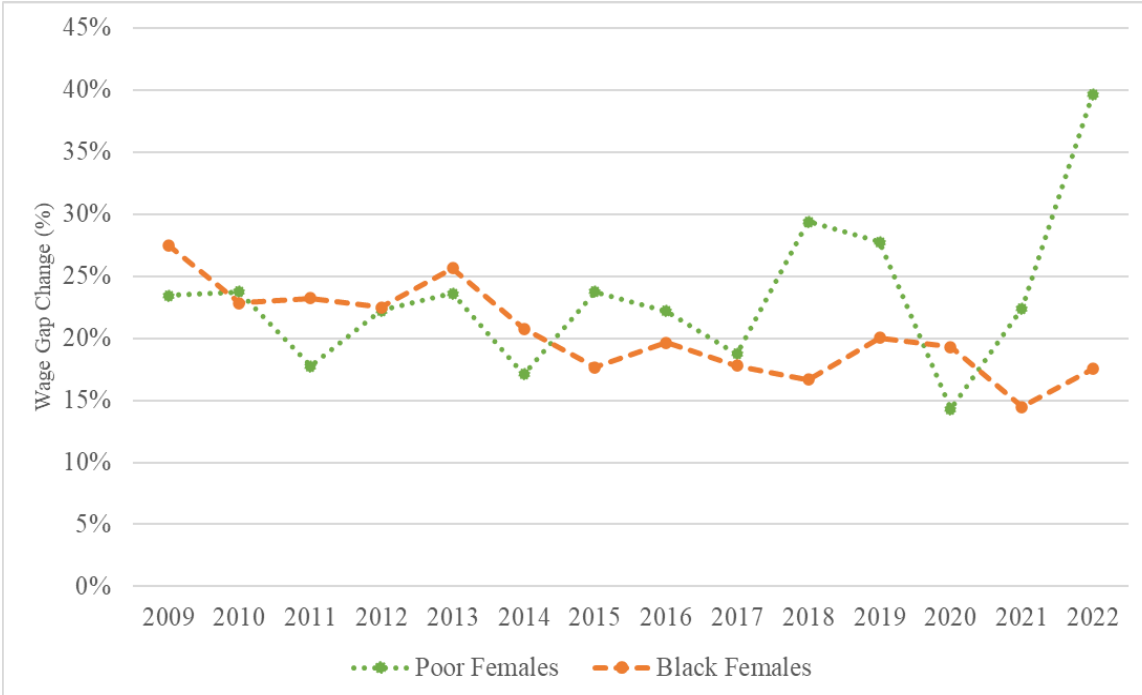
Has Child (Less than Five Years Old); Figure A4, Tables A2 and A3

Figures 7 and A4 shows that women with children less than five years old, compared to men with children less than five years old, experience approximately 15% lower wages. We also see that women with children less than five years old have increased their wages from 2009 to 2022 by approximately eight percent. As COVID-19 began, these women increased their wages by only one percent, with a decrease from 2021 to 2022. Because the overall value of this line lies in the negative, it indicates that women with children less than five years old experience decreasing wages compared to men with children under five years old. The wage discrepancy between men and women is higher for individuals with children of all ages compared to individuals with children less than five years old.

Is Married; Figure A10, Tables A8 and A9

Figures 7 and A10 shows that married women experience approximately 30% lower wages than married men. Figure A10 shows that married women's wages have increased from 2009 to 2022, showing that married women have been making wage gains compared to married men over time. This is especially true from 2009 to 2014. COVID-19 has caused married women's wages to increase. Single women have higher income levels than married women (refer to Figure 5) but experienced stagnating wages during COVID-19. This could indicate that married women's industries were less impacted by the coronavirus pandemic compared to single women's industries.

Figure 8: Variable Specific Female Wages: Poor Females and Black Females



Source: IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

Is Poor; Figure A6, Tables A4 and A5

Based on the results of Figure 8, we see that poverty does not have a large impact on the level of women's wages over time. Thus, when looking at poor women's wages over time, it is important to note that this sample does not have a large impact on overall women's wages. When looking at Figure A6, we can see that poor women have higher wages than poor men by approximately 25%. There is a sharp increase as COVID-19 begins, with the largest jump occurring from 2020 to 2022. Thus, we can conclude that poor women have increased their wages during the COVID-19 period compared to poor men.

Race (Is Black); Figure A8, Tables A6 and A7

Similar to poverty, based on Figure 8, we see that race does not have a large impact on the level of women's wages over time. Thus, when looking at Black women's wages over time, it is important to note that this sample does not have a large impact on overall women's wages. Figure A8 shows that Black women, compared to Black men, have approximately 20% higher wages. Looking at Figure A8, we see that Black women's wages have dropped from 2009 to 2022, decreasing by nine percent. This does not follow along with the literature as it was found that Black men are paid $0.71 for every dollar paid to white men, and Black women are paid $0.63 for every dollar paid to white men. This is a sample error wherein my data sample includes Black women that have wages higher than Black men. This anomaly shows imperfect data and should be investigated in a further edition of this research study.

V. Future Research

While the results of this research study are promising, there were definitely several limitations when performing the data analysis that should be adjusted in future versions of this experiment. First, additional data points should be used per year to make the sample chosen more representative of the United States population. Secondly, due to the specifications from the ASEC, data was only collected from the month of March. In order to better capture income levels from later months of COVID-19, additional data would be required. Another key limitation of this research study is the choice of independent variables used. Log of wages, in wage study regressions, is a constant that has been established through numerous research papers mentioned above, and is not subject to change. On the other hand, independent variables such as education, experience, labor force participation rates, child status, etc. can be altered and vary based on the specifications of each research study. Due to time constraints and data processing limitations, not all relevant variables were included in the regression analysis. Variables such as industry, occupation, competitive drive, etc. were left out of this research study but could have strong impacts on changing levels of the gender wage gap, helping to further explain what factors have positive and negative returns to the labor market. Future research expanding on the results of this research study would help to analyze different aspects of the gender wage gap.

The results of this study, specifically related to COVID-19 trend analyses, have policy implications. Advocates of equal pay between men and women can point to different factors within this research study that correlate to lower wages for women to focus on certain aspects of society that contribute most strongly to wage discrepancies.

For example, we find that marital status has a bigger impact on wages for women than child status, but COVID-19 wage changes were primarily caused by women without children. Policy changes addressing childcare support could be made a priority during the coronavirus pandemic. Following the pandemic, policy propositions could transition to marital status wage discrepancy issues. Additionally, future research related to the study above can be carried out by changing the dependent variable from wages to performance, well-being, employment rates, happiness levels, etc. to determine the effects the pandemic has had on different aspects of the labor market and work life.

VI. Conclusion

This thesis has three main takeaways:

First, COVID-19, as opposed to predictions from Alon et al. (2020), caused women's wages to rise relative to men's (Rosalsky, 2020). Based on the results of the empirical research study in this paper, when controlling for standard wage explanatory variables, the gender wage gap was reduced by 3.12% during COVID-19 (Chatterjee, 2022). This is significant because societal changes during the coronavirus pandemic have actually helped women earn relatively higher wages. Prior to COVID-19, Figure 2 shows that in the aftermath of the 2007 recession, the gender wage gap decreased, but slowly widened until 2016.

Second, we find that the wage premium for men is primarily driven by marital status, followed closely by child status. Model III shows that married women have the largest wage gap out of the tested factors, with single women having 19% higher wages when controlling for married women. Childless women have 15% higher wages when controlling for women with children of any age. It has been well documented by many, including Perry (2021), Kalenkoski (2022), Collins (2020), etc., that marital status and child status play a role as determinants of the gender wage gap, but no study has argued that one plays a bigger role than the other in affecting the wage premium. This research paper empirically ranks marital status over child status as a bigger indication of gender disparity. Thus, when a woman gets married, we find that their wages drop even more than when they have children of any age. Marital status and child status are often linked, as married women tend to have more children than single women. Thus, we find that married women who have children experience a combination effect that further drops their wages.

Third, the growth in the gender wage gap during COVID-19 was primarily caused by child status compared to marital status, as the wage gap fell more for women with no children than for single females. We find that women with children under the age of five have seen reduced wages during COVID-19, a trend that is not seen in women with children of any age. This supports the literature that increased child support has hurt women during the coronavirus pandemic, and further shows that younger children have an even worse impact on women's wages. Kleven (2019) finds that childless women earn salaries that are very similar to men's salaries, and women with children experience a high wage gap, which is supported by this paper. Furthermore, during COVID-19, married women made wage gains compared to married men. This indicates that industries that married women most commonly work in were impacted less by COVID-19 than the industries married men typically work. While the literature states that as a whole, industries with more women were more heavily impacted by COVID-19, the data in this research study show that industries with *married* women majorities were impacted less than married men. We find that COVID-19 is helping to reverse this trend due to possible industry differences between married men and women.

Poverty and race have smaller effects as determinants of the gender wage gap. We find that non-poor women have a slightly lower wage gap than poor women. Model III shows that non-poor women have 2% higher wages than poor women. Poor women have significantly higher wages than poor men, a trend that has accelerated during COVID-19. A possible explanation for this is that poor men tend to work in occupations that require manual labor whereas poor women tend to work in more digital, consumer-oriented jobs. Thus, because the coronavirus pandemic shifted work to a remote model, poor women would likely have seen gains in their necessity due to added technological skills compared to poor men. Race does not play a major factor in the gender wage gap as Model II shows virtually no difference in female wages when controlling for Black women.

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U.S. Census Bureau. (2022). Current Population Survey, Annual Social and Economic (ASEC) Supplement: Table PINC-05: Work Experience in 2021 – People 15 Years Old and Over by Total Money Earnings in 2021, Age, Race, Hispanic Origin, Sex, and Disability Status. https://www.census.gov/data/tables/time-series/demo/income-poverty/cps-pinc/pinc05.html

VIII. Appendix

Source: all figures and tables from IPUMS CPS Annual Social and Economics (ASEC) Survey, author's calculation

Figure A1: Overall Female Wages: Females with no Children vs. Baseline Wage Gap

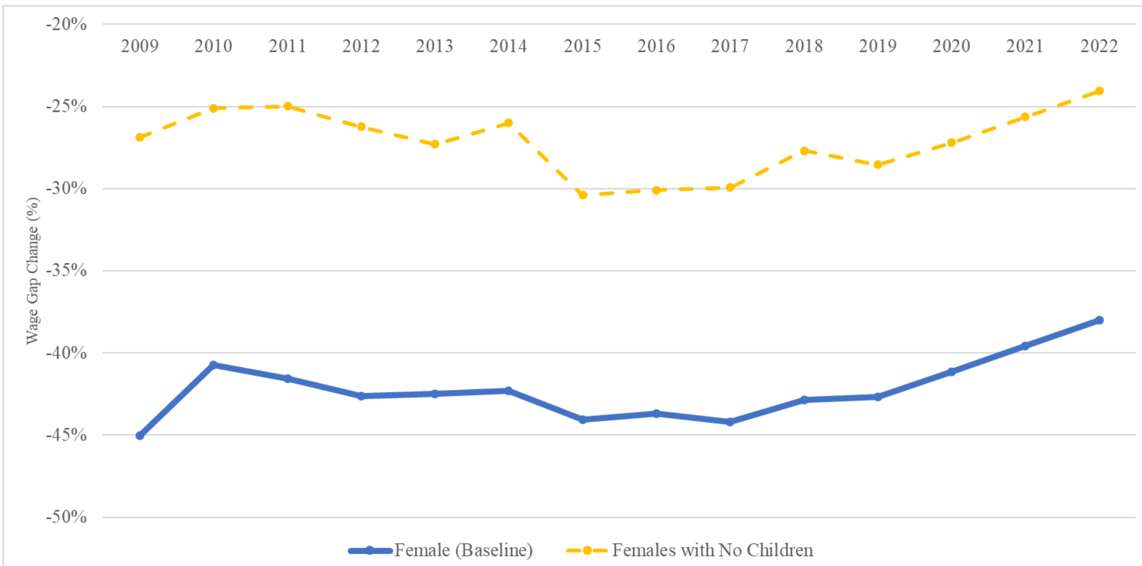

Figure A2: Females with Child (All) Wages

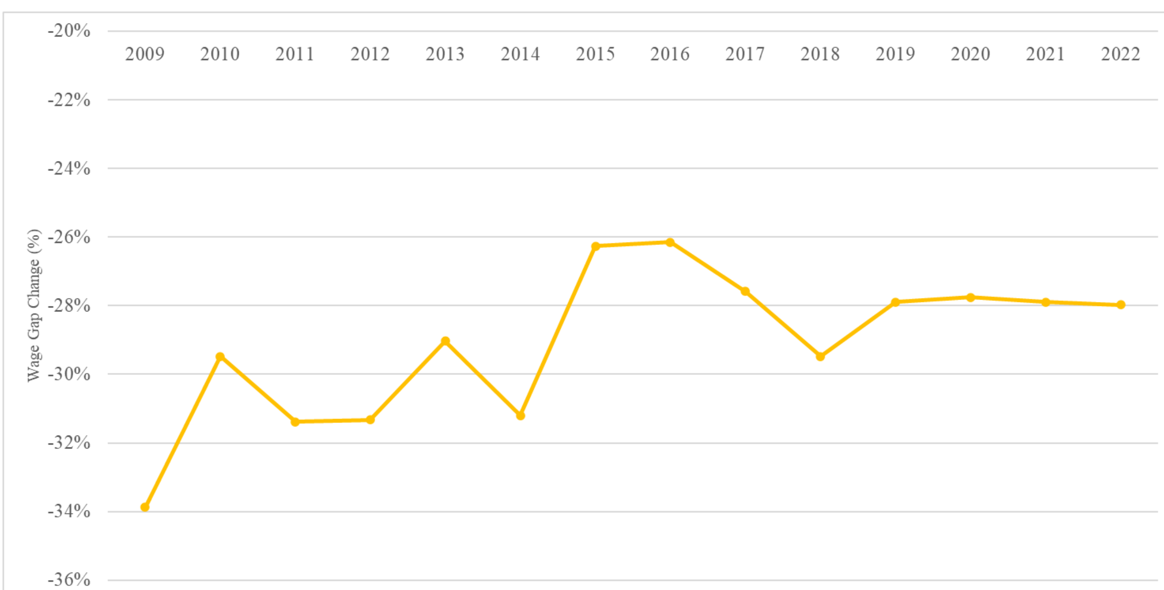

Table A1: Controlling for Has.Child_Female (all) vs. Baseline

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_2009	−0.006 (0.008)	−0.027*** (0.009)
Is_2010	−0.073*** (0.008)	−0.083*** (0.009)
Is_2011	−0.098*** (0.008)	−0.112*** (0.009)
Is_2012	−0.095*** (0.008)	−0.109*** (0.009)
Is_2013	−0.086*** (0.008)	−0.093*** (0.009)
Is_2014	−0.075*** (0.008)	−0.087*** (0.009)
Is_2015	−0.035*** (0.008)	−0.036*** (0.009)
Is_2016	−0.003 (0.008)	−0.003 (0.009)
Is_2017	0.023*** (0.008)	0.020** (0.009)
Is_2018	0.023*** (0.008)	0.016* (0.009)
Is_2019	0.054*** (0.008)	0.051*** (0.009)
Is_2020	0.058*** (0.008)	0.057*** (0.009)
Is_2021	−0.0001 (0.008)	−0.001 (0.009)
Is_2022		
Is_Female_2009	−0.457*** (0.006)	−0.269*** (0.009)
Is_Female_2010	−0.415*** (0.006)	−0.251*** (0.009)
Is_Female_2011	−0.423*** (0.006)	−0.250*** (0.009)
Is_Female_2012	−0.434*** (0.006)	−0.262*** (0.009)
Is_Female_2013	−0.431*** (0.006)	−0.273*** (0.009)
Is_Female_2014	−0.429*** (0.006)	−0.260*** (0.009)
Is_Female_2015	−0.447*** (0.006)	−0.304*** (0.009)
Is_Female_2016	−0.442*** (0.006)	−0.301*** (0.009)
Is_Female_2017	−0.446*** (0.006)	−0.299*** (0.009)
Is_Female_2018	−0.433*** (0.006)	−0.277*** (0.009)
Is_Female_2019	−0.430*** (0.006)	−0.286*** (0.009)
Is_Female_2020	−0.416*** (0.007)	−0.272*** (0.010)
Is_Female_2021	−0.400*** (0.007)	−0.256*** (0.010)
Is_Female_2022	−0.384*** (0.007)	−0.241*** (0.010)
Is_Child_2009	0.115*** (0.006)	0.275*** (0.008)
Is_Child_2010	0.129*** (0.006)	0.268*** (0.008)
Is_Child_2011	0.125*** (0.006)	0.273*** (0.008)
Is_Child_2012	0.139*** (0.006)	0.287*** (0.008)
Is_Child_2013	0.123*** (0.006)	0.260*** (0.008)
Is_Child_2014	0.123*** (0.006)	0.269*** (0.008)
Is_Child_2015	0.119*** (0.006)	0.243*** (0.008)
Is_Child_2016	0.100*** (0.006)	0.223*** (0.009)
Is_Child_2017	0.086*** (0.006)	0.216*** (0.009)
Is_Child_2018	0.084*** (0.006)	0.224*** (0.009)
Is_Child_2019	0.073*** (0.006)	0.206*** (0.009)
Is_Child_2020	0.088*** (0.007)	0.220*** (0.009)
Is_Child_2021	0.078*** (0.007)	0.210*** (0.009)
Is_Child_2022	0.066*** (0.007)	0.198*** (0.010)
Is_Child_Female_2009		−0.339*** (0.012)
Is_Child_Female_2010		−0.295*** (0.012)
Is_Child_Female_2011		−0.314*** (0.012)
Is_Child_Female_2012		−0.313*** (0.012)
Is_Child_Female_2013		−0.290*** (0.012)
Is_Child_Female_2014		−0.312*** (0.012)
Is_Child_Female_2015		−0.263*** (0.012)
Is_Child_Female_2016		−0.262*** (0.013)
Is_Child_Female_2017		−0.276*** (0.013)
Is_Child_Female_2018		−0.295*** (0.013)
Is_Child_Female_2019		−0.279*** (0.013)
Is_Child_Female_2020		0.278*** (0.014)
Is_Child_Female_2021		−0.279*** (0.013)
Is_Child_Female_2022		−0.280*** (0.014)
Educ	0.153*** (0.0003)	0.152*** (0.0003)
Experience	0.082*** (0.0004)	0.083*** (0.0004)
Experience_Sqrd	−0.001*** (0.00001)	−0.001*** (0.00001)
Is_Black	−0.127*** (0.003)	−0.122*** (0.003)
Constant	7.441*** (0.008)	7.386*** (0.009)
Observations	1,090,039	1,090,039
R^2	0.286	0.291
Adjusted R^2	0.286	0.291
Residual Std. Error	0.869 (df = 1089993)	0.866 (df = 1089979)
F Statistic	9,705.790*** (df = 45; 1089993)	7,585.143*** (df = 59; 1089979)
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01

Figure A3: Overall Female Wages: Females with Children > 5 Years vs. Baseline Wage Gap

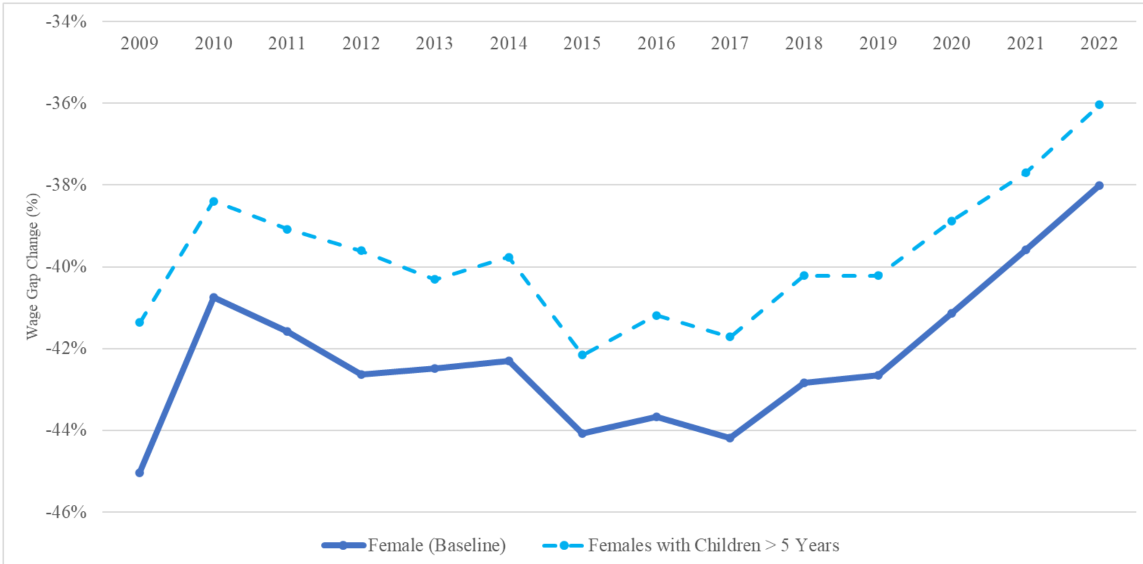

Figure A4: Females with Child (< 5 Years) Wages

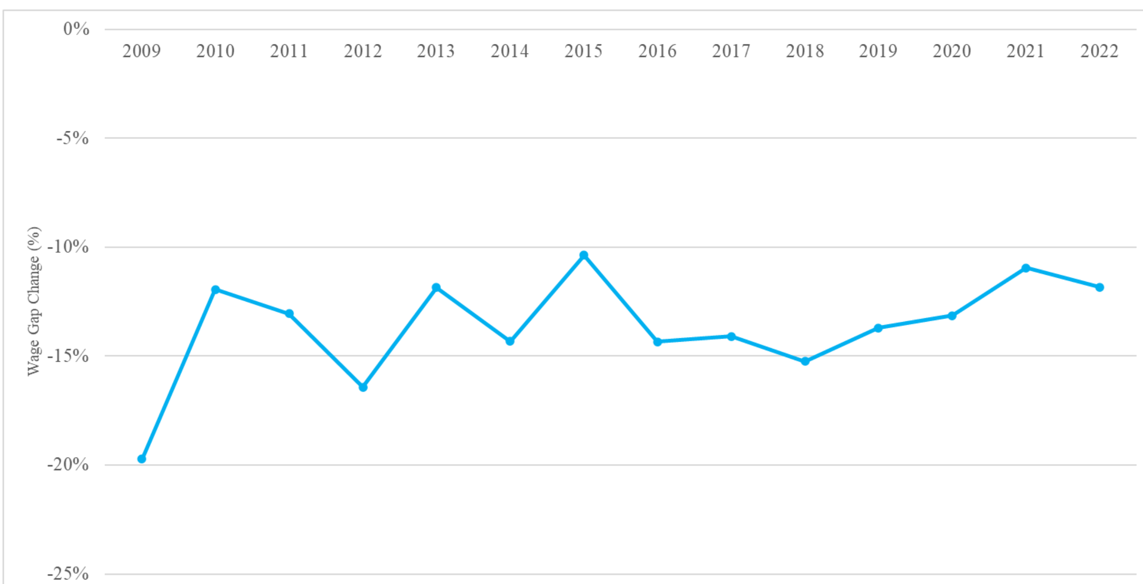

Table A2: Controlling for Has.Child_Female (< 5 Years) vs. Baseline - Condensed

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_Female_2009	−0.447*** (0.006)	−0.414*** (0.006)
Is_Female_2010	−0.404*** (0.006)	−0.384*** (0.006)
Is_Female_2011	−0.413*** (0.006)	−0.391*** (0.007)
Is_Female_2012	−0.423*** (0.006)	−0.396*** (0.007)
Is_Female_2013	−0.422*** (0.006)	−0.403*** (0.007)
Is_Female_2014	−0.420*** (0.006)	−0.398*** (0.007)
Is_Female_2015	−0.438*** (0.006)	−0.422*** (0.007)
Is_Female_2016	−0.434*** (0.006)	−0.412*** (0.007)
Is_Female_2017	−0.439*** (0.006)	−0.417*** (0.007)
Is_Female_2018	−0.425*** (0.006)	−0.402*** (0.007)
Is_Female_2019	−0.423*** (0.006)	−0.402*** (0.007)
Is_Female_2020	−0.409*** (0.007)	−0.389*** (0.007)
Is_Female_2021	−0.393*** (0.007)	−0.377*** (0.007)
Is_Female_2022	−0.378*** (0.007)	−0.360*** (0.008)
Is_Child_Female_2009		−0.197*** (0.016)
Is_Child_Female_2010		−0.119*** (0.016)
Is_Child_Female_2011		−0.131*** (0.016)
Is_Child_Female_2012		−0.164*** (0.016)
Is_Child_Female_2013		−0.119*** (0.016)
Is_Child_Female_2014		−0.143*** (0.017)
Is_Child_Female_2015		−0.104*** (0.017)
Is_Child_Female_2016		−0.144*** (0.017)
Is_Child_Female_2017		−0.141*** (0.017)
Is_Child_Female_2018		−0.152*** (0.018)
Is_Child_Female_2019		−0.137*** (0.018)
Is_Child_Female_2020		−0.131*** (0.019)
Is_Child_Female_2021		−0.109*** (0.019)
Is_Child_Female_2022		−0.118*** (0.020)
Constant	7.353*** (0.008)	7.351*** (0.008)
Observations	1,090,039	1,090,039
R^2	0.287	0.287
Adjusted R^2	0.287	0.287
Residual Std. Error	0.868 (df = 1089993)	0.868 (df = 1089979)
F Statistic	9,732.968*** (df = 45; 1089993)	7,445.555*** (df = 59; 1089979)
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01

Table A3: Controlling for Has.Child_Female (< 5 Years) vs. Baseline

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_2009	0.016^{**} (0.007)	0.009 (0.007)
Is_2010	-0.044^{***} (0.007)	-0.045^{***} (0.007)
Is_2011	-0.068^{***} (0.007)	-0.070^{***} (0.007)
Is_2012	-0.060^{***} (0.007)	-0.065^{***} (0.007)
Is_2013	-0.060^{***} (0.007)	-0.060^{***} (0.007)
Is_2014	-0.047^{***} (0.007)	-0.049^{***} (0.007)
Is_2015	−0.008 (0.007)	−0.007 (0.007)
Is_2016	0.015^{**} (0.007)	0.013^{*} (0.007)
Is_2017	0.035^{***} (0.007)	0.033^{***} (0.007)
Is_2018	0.032^{***} (0.007)	0.029^{***} (0.007)
Is_2019	0.057^{***} (0.007)	0.055^{***} (0.007)
Is_2020	0.069^{***} (0.007)	0.067^{***} (0.007)
Is_2021	0.005 (0.007)	0.005 (0.007)
Is_2022		
Is_Female_2009	-0.447^{***} (0.006)	-0.414^{***} (0.006)
Is_Female_2010	-0.404^{***} (0.006)	-0.384^{***} (0.006)
Is_Female_2011	-0.413^{***} (0.006)	-0.391^{***} (0.007)
Is_Female_2012	-0.423^{***} (0.006)	-0.396^{***} (0.007)
Is_Female_2013	-0.422^{***} (0.006)	-0.403^{***} (0.007)
Is_Female_2014	-0.420^{***} (0.006)	-0.398^{***} (0.007)
Is_Female_2015	-0.438^{***} (0.006)	-0.422^{***} (0.007)
Is_Female_2016	-0.434^{***} (0.006)	-0.412^{***} (0.007)
Is_Female_2017	-0.439^{***} (0.006)	-0.417^{***} (0.007)
Is_Female_2018	-0.425^{***} (0.006)	-0.402^{***} (0.007)
Is_Female_2019	-0.423^{***} (0.006)	-0.402^{***} (0.007)
Is_Female_2020	-0.409^{***} (0.007)	-0.389^{***} (0.007)
Is_Female_2021	-0.393^{***} (0.007)	-0.377^{***} (0.007)
Is_Female_2022	-0.378^{***} (0.007)	-0.360^{***} (0.008)
Is_Child_2009	0.162^{***} (0.008)	0.251^{***} (0.010)
Is_Child_2010	0.164^{***} (0.008)	0.218^{***} (0.011)
Is_Child_2011	0.148^{***} (0.008)	0.207^{***} (0.011)
Is_Child_2012	0.164^{***} (0.008)	0.238^{***} (0.011)
Is_Child_2013	0.171^{***} (0.008)	0.225^{***} (0.011)
Is_Child_2014	0.158^{***} (0.008)	0.223^{***} (0.011)
Is_Child_2015	0.152^{***} (0.008)	0.199^{***} (0.011)
Is_Child_2016	0.146^{***} (0.009)	0.211^{***} (0.012)
Is_Child_2017	0.138^{***} (0.009)	0.201^{***} (0.012)
Is_Child_2018	0.152^{***} (0.009)	0.220^{***} (0.012)
Is_Child_2019	0.152^{***} (0.009)	0.214^{***} (0.012)
Is_Child_2020	0.155^{***} (0.009)	0.215^{***} (0.013)
Is_Child_2021	0.160^{***} (0.010)	0.210^{***} (0.013)
Is_Child_2022	0.155^{***} (0.010)	0.209^{***} (0.013)
Is_Child_Female_2009		-0.197^{***} (0.016)
Is_Child_Female_2010		-0.119^{***} (0.016)
Is_Child_Female_2011		-0.131^{***} (0.016)
Is_Child_Female_2012		-0.164^{***} (0.016)
Is_Child_Female_2013		-0.119^{***} (0.016)
Is_Child_Female_2014		-0.143^{***} (0.017)
Is_Child_Female_2015		-0.104^{***} (0.017)
Is_Child_Female_2016		-0.144^{***} (0.017)
Is_Child_Female_2017		-0.141^{***} (0.017)
Is_Child_Female_2018		-0.152^{***} (0.018)
Is_Child_Female_2019		-0.137^{***} (0.018)
Is_Child_Female_2020		-0.131^{***} (0.019)
Is_Child_Female_2021		-0.109^{***} (0.019)
Is_Child_Female_2022		-0.118^{***} (0.020)
Educ	0.153^{***} (0.0003)	0.153^{***} (0.0003)
Experience	0.089^{***} (0.0003)	0.088^{***} (0.0003)
Experience_Sqrd	-0.001^{***} (0.00001)	-0.001^{***} (0.00001)
Is_Black	-0.130^{***} (0.003)	-0.129^{***} (0.003)
Constant	7.353^{***} (0.008)	7.351^{***} (0.008)
Observations	1,090,039	1,090,039
R^2	0.287	0.287
Adjusted R^2	0.287	0.287
Residual Std. Error	0.868 (df = 1089993)	0.868 (df = 1089979)
F Statistic	$9{,}732.968^{***}$ (df = 45; 1089993)	$7{,}445.555^{***}$ (df = 59; 1089979)
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01

Figure A5: Overall Female Wages: Non-Poor Females vs. Baseline Wage Gap

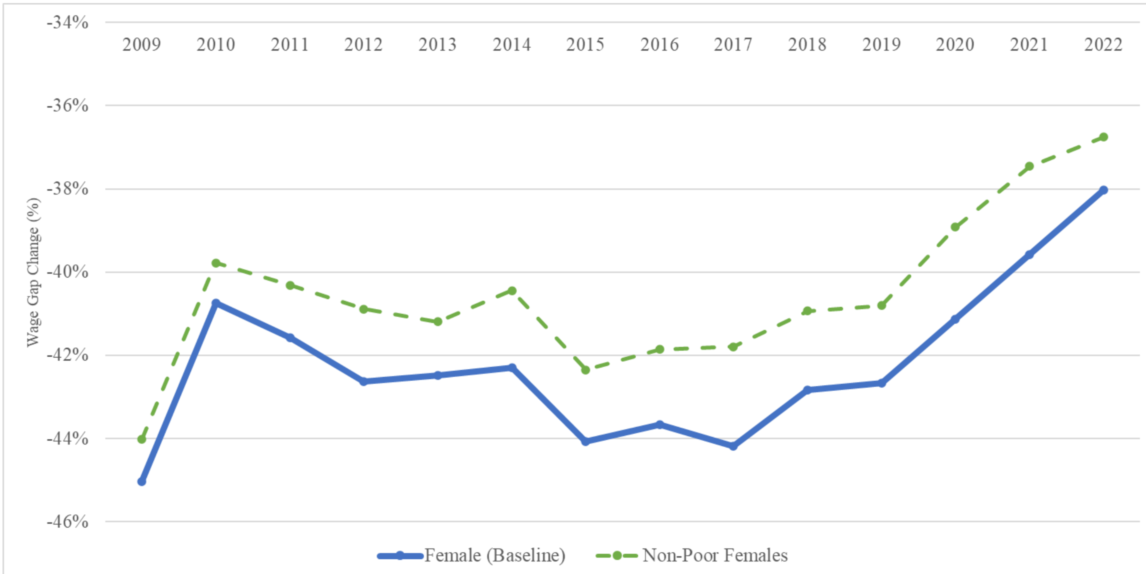

Figure A6: Poor Female Wages

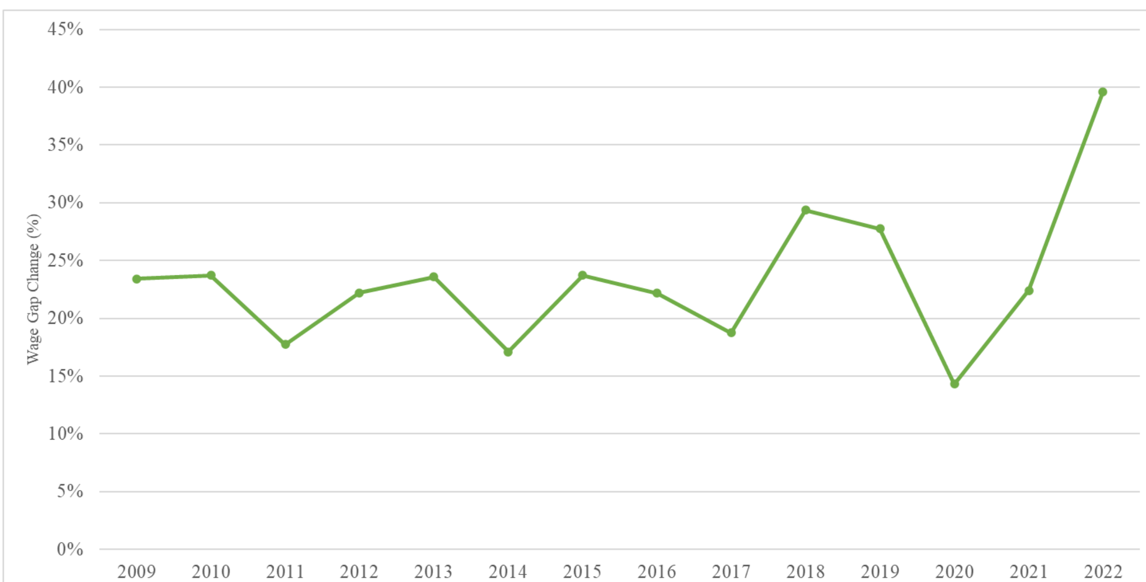

Table A4: Controlling for If.Poor_Female vs. Baseline - Condensed

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_Female_2009	-0.427^{***} (0.006)	-0.440^{***} (0.006)
Is_Female_2010	-0.383^{***} (0.006)	-0.398^{***} (0.006)
Is_Female_2011	-0.392^{***} (0.006)	-0.403^{***} (0.006)
Is_Female_2012	-0.395^{***} (0.006)	-0.409^{***} (0.006)
Is_Female_2013	-0.397^{***} (0.006)	-0.412^{***} (0.006)
Is_Female_2014	-0.394^{***} (0.006)	-0.404^{***} (0.006)
Is_Female_2015	-0.409^{***} (0.006)	-0.424^{***} (0.006)
Is_Female_2016	-0.407^{***} (0.006)	-0.419^{***} (0.006)
Is_Female_2017	-0.409^{***} (0.006)	-0.418^{***} (0.006)
Is_Female_2018	-0.396^{***} (0.006)	-0.409^{***} (0.006)
Is_Female_2019	-0.396^{***} (0.006)	-0.408^{***} (0.006)
Is_Female_2020	-0.384^{***} (0.006)	-0.389^{***} (0.007)
Is_Female_2021	-0.366^{***} (0.006)	-0.375^{***} (0.007)
Is_Female_2022	-0.352^{***} (0.007)	-0.367^{***} (0.007)
IsIn_Poverty_Female_2009		0.234^{***} (0.024)
IsIn_Poverty_Female_2010		0.237^{***} (0.023)
IsIn_Poverty_Female_2011		0.177^{***} (0.023)
IsIn_Poverty_Female_2012		0.222^{***} (0.024)
IsIn_Poverty_Female_2013		0.236^{***} (0.024)
IsIn_Poverty_Female_2014		0.171^{***} (0.024)
IsIn_Poverty_Female_2015		0.237^{***} (0.024)
IsIn_Poverty_Female_2016		0.222^{***} (0.026)
IsIn_Poverty_Female_2017		0.187^{***} (0.027)
IsIn_Poverty_Female_2018		0.294^{***} (0.029)
IsIn_Poverty_Female_2019		0.278^{***} (0.029)
IsIn_Poverty_Female_2020		0.143^{***} (0.033)
IsIn_Poverty_Female_2021		0.224^{***} (0.033)
IsIn_Poverty_Female_2022		0.396^{***} (0.034)
Constant	7.755^{***} (0.007)	7.763^{***} (0.007)
Observations	1,090,039	1,090,039
R^2	0.357	0.358
Adjusted R^2	0.357	0.358
Residual Std. Error	0.824 (df = 1089993)	0.824 (df = 1089979)
F Statistic	$13{,}447.320^{***}$ (df = 45; 1089993)	$10{,}285.180^{***}$ (df = 59; 1089979)
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01

Table A5: Controlling for Is.Poor_Female vs. Baseline

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_2009	0.023*** (0.006)	0.022*** (0.006)
Is_2010	−0.029*** (0.006)	−0.030*** (0.006)
Is_2011	−0.053*** (0.006)	−0.056*** (0.006)
Is_2012	−0.045*** (0.006)	−0.046*** (0.006)
Is_2013	−0.042*** (0.006)	−0.042*** (0.006)
Is_2014	−0.032*** (0.006)	−0.034*** (0.006)
Is_2015	0.002 (0.006)	0.001 (0.006)
Is_2016	0.022*** (0.006)	0.021*** (0.006)
Is_2017	0.036*** (0.006)	0.033*** (0.006)
Is_2018	0.030*** (0.006)	0.029*** (0.006)
Is_2019	0.054*** (0.006)	0.053*** (0.006)
Is_2020	0.071*** (0.006)	0.066*** (0.007)
Is_2021	0.005 (0.006)	0.002 (0.006)
Is_2022		
Is_Female_2009	−0.427*** (0.006)	−0.440*** (0.006)
Is_Female_2010	−0.383*** (0.006)	−0.398*** (0.006)
Is_Female_2011	−0.392*** (0.006)	−0.403*** (0.006)
Is_Female_2012	−0.395*** (0.006)	−0.409*** (0.006)
Is_Female_2013	−0.397*** (0.006)	−0.412*** (0.006)
Is_Female_2014	−0.394*** (0.006)	−0.404*** (0.006)
Is_Female_2015	−0.409*** (0.006)	−0.424*** (0.006)
Is_Female_2016	−0.407*** (0.006)	−0.419*** (0.006)
Is_Female_2017	−0.409*** (0.006)	−0.418*** (0.006)
Is_Female_2018	−0.396*** (0.006)	−0.409*** (0.006)
Is_Female_2019	−0.396*** (0.006)	−0.408*** (0.006)
Is_Female_2020	−0.384*** (0.006)	−0.389*** (0.007)
Is_Female_2021	−0.366*** (0.006)	−0.375*** (0.007)
Is_Female_2022	−0.352*** (0.007)	−0.367*** (0.007)
IsIn_Poverty_2009	−1.210*** (0.012)	−1.338*** (0.018)
IsIn_Poverty_2010	−1.208*** (0.012)	−1.337*** (0.017)
IsIn_Poverty_2011	−1.203*** (0.012)	−1.299*** (0.017)
IsIn_Poverty_2012	−1.238*** (0.012)	−1.362*** (0.018)
IsIn_Poverty_2013	−1.200*** (0.012)	−1.329*** (0.017)
IsIn_Poverty_2014	−1.228*** (0.012)	−1.322*** (0.018)
IsIn_Poverty_2015	−1.201*** (0.012)	−1.334*** (0.018)
IsIn_Poverty_2016	−1.262*** (0.013)	−1.386*** (0.020)
IsIn_Poverty_2017	−1.283*** (0.014)	−1.391*** (0.021)
IsIn_Poverty_2018	−1.289*** (0.014)	−1.460*** (0.022)
IsIn_Poverty_2019	−1.265*** (0.015)	−1.426*** (0.022)
IsIn_Poverty_2020	−1.441*** (0.017)	−1.523*** (0.025)
IsIn_Poverty_2021	−1.392*** (0.016)	−1.520*** (0.025)
IsIn_Poverty_2022	−1.429*** (0.017)	−1.650*** (0.025)
IsIn_Poverty_Female_2009		0.234*** (0.024)
IsIn_Poverty_Female_2010		0.237*** (0.023)
IsIn_Poverty_Female_2011		0.177*** (0.023)
IsIn_Poverty_Female_2012		0.222*** (0.024)
IsIn_Poverty_Female_2013		0.236*** (0.024)
IsIn_Poverty_Female_2014		0.171*** (0.024)
IsIn_Poverty_Female_2015		0.237*** (0.024)
IsIn_Poverty_Female_2016		0.222*** (0.026)
IsIn_Poverty_Female_2017		0.187*** (0.027)
IsIn_Poverty_Female_2018		0.294*** (0.029)
IsIn_Poverty_Female_2019		0.278*** (0.029)
IsIn_Poverty_Female_2020		0.143*** (0.033)
IsIn_Poverty_Female_2021		0.224*** (0.033)
IsIn_Poverty_Female_2022		0.396*** (0.034)
Educ	0.133*** (0.0003)	0.133*** (0.0003)
Experience	0.089*** (0.0003)	0.089*** (0.0003)
Experience_Sqrd	−0.001*** (0.00001)	−0.001*** (0.00001)
Is_Black	−0.091*** (0.002)	−0.093*** (0.002)
Constant	7.755*** (0.007)	7.763*** (0.007)
Observations	1,090,039	1,090,039
R^2	0.357	0.358
Adjusted R^2	0.357	0.358
Residual Std. Error	0.824 (df = 1089993)	0.824 (df = 1089979)
F Statistic	13,447.320*** (df = 45; 1089993)	10,285.180*** (df = 59; 1089979)
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01

Figure A7: Overall Female Wages: Non-Black Females vs. Baseline Wage Gap

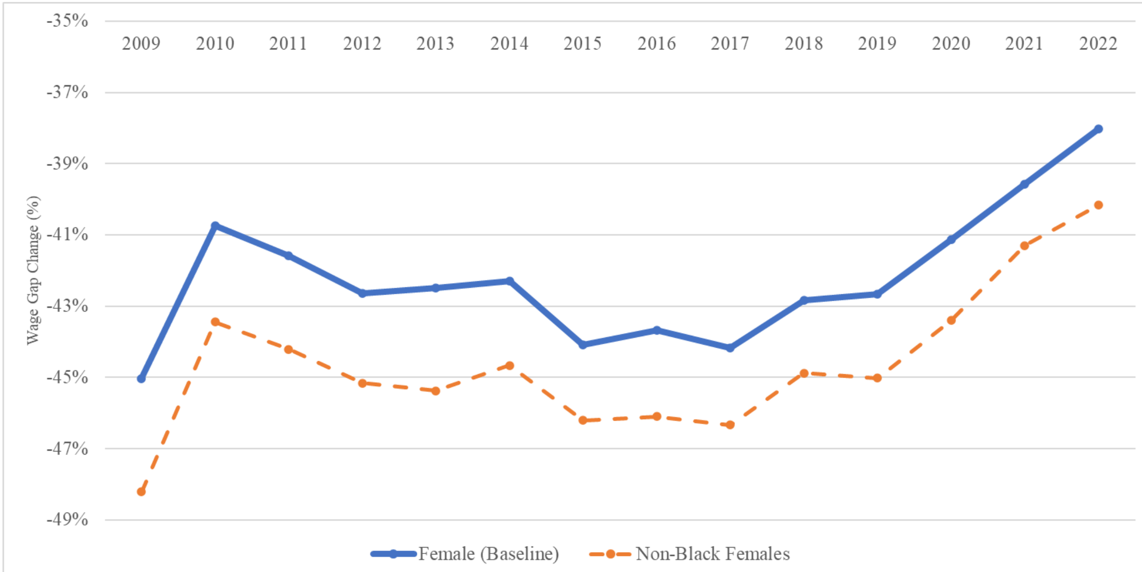

Figure A8: Black Female Wages

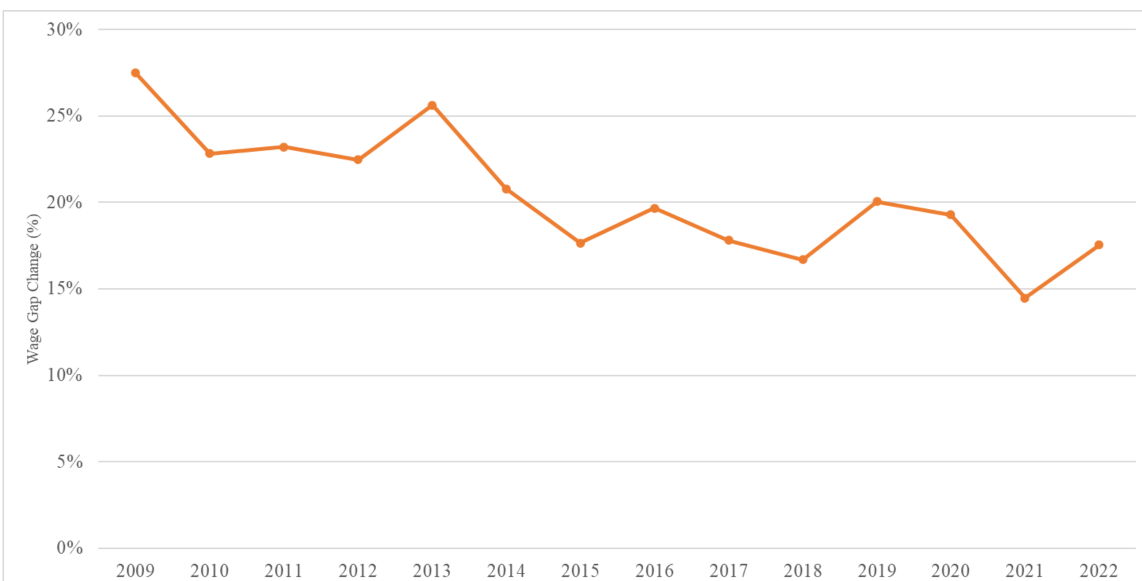

Table A6: Controlling for If.Black_Female vs. Baseline - Condensed

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_Female_2009	−0.452*** (0.006)	−0.482*** (0.006)
Is_Female_2010	−0.408*** (0.006)	−0.434*** (0.006)
Is_Female_2011	−0.416*** (0.006)	−0.442*** (0.006)
Is_Female_2012	−0.426*** (0.006)	−0.452*** (0.006)
Is_Female_2013	−0.425*** (0.006)	−0.454*** (0.006)
Is_Female_2014	−0.422*** (0.006)	−0.447*** (0.006)
Is_Female_2015	−0.441*** (0.006)	−0.462*** (0.006)
Is_Female_2016	−0.437*** (0.006)	−0.461*** (0.007)
Is_Female_2017	−0.442*** (0.006)	−0.463*** (0.007)
Is_Female_2018	−0.428*** (0.006)	−0.449*** (0.007)
Is_Female_2019	−0.426*** (0.006)	−0.450*** (0.007)
Is_Female_2020	−0.412*** (0.007)	−0.434*** (0.007)
Is_Female_2021	−0.395*** (0.007)	−0.413*** (0.007)
Is_Female_2022	−0.380*** (0.007)	−0.402*** (0.007)
Is_Race_Female_2009		0.275*** (0.019)
Is_Race_Female_2010		0.228*** (0.018)
Is_Race_Female_2011		0.232*** (0.019)
Is_Race_Female_2012		0.225*** (0.019)
Is_Race_Female_2013		0.256*** (0.019)
Is_Race_Female_2014		0.208*** (0.019)
Is_Race_Female_2015		0.176*** (0.019)
Is_Race_Female_2016		0.197*** (0.019)
Is_Race_Female_2017		0.178*** (0.019)
Is_Race_Female_2018		0.167*** (0.019)
Is_Race_Female_2019		0.201*** (0.020)
Is_Race_Female_2020		0.193*** (0.021)
Is_Race_Female_2021		0.145*** (0.021)
Is_Race_Female_2022		0.175*** (0.021)
Constant	−4,571,318.000 (3.04e7)	−4,024,120.000 (3.03e7)
Observations	1,090,039	1,090,039
Log Likelihood	−1,395,015.000	−1,394,206.000
Akaike Inf. Crit.	2,790,123.000	2,788,532.000
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01

Table A7: Controlling for Is.Black_Female vs. Baseline

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_2009	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2010	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2011	4,571,325.000 (3.04e7)	4,024,127.000 (3.03e7)
Is_2012	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2013	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2014	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2015	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2016	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2017	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2018	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2019	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2020	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2021	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_2022	4,571,325.000 (3.04e7)	4,024,128.000 (3.03e7)
Is_Female_2009	−0.452*** (0.006)	−0.482*** (0.006)
Is_Female_2010	−0.408*** (0.006)	−0.434*** (0.006)
Is_Female_2011	−0.416*** (0.006)	−0.442*** (0.006)
Is_Female_2012	−0.426*** (0.006)	−0.452*** (0.006)
Is_Female_2013	−0.425*** (0.006)	−0.454*** (0.006)
Is_Female_2014	−0.422*** (0.006)	−0.447*** (0.006)
Is_Female_2015	−0.441*** (0.006)	−0.462*** (0.006)
Is_Female_2016	−0.437*** (0.006)	−0.461*** (0.007)
Is_Female_2017	−0.442*** (0.006)	−0.463*** (0.007)
Is_Female_2018	−0.428*** (0.006)	−0.449*** (0.007)
Is_Female_2019	−0.426*** (0.006)	−0.450*** (0.007)
Is_Female_2020	−0.412*** (0.007)	−0.434*** (0.007)
Is_Female_2021	−0.395*** (0.007)	−0.413*** (0.007)
Is_Female_2022	−0.380*** (0.007)	−0.402*** (0.007)
Is_Race_2009	−0.099*** (0.009)	−0.249*** (0.014)
Is_Race_2010	−0.104*** (0.009)	−0.228*** (0.014)
Is_Race_2011	−0.127*** (0.009)	−0.253*** (0.014)
Is_Race_2012	−0.136*** (0.010)	−0.258*** (0.014)
Is_Race_2013	−0.144*** (0.009)	−0.282*** (0.014)
Is_Race_2014	−0.150*** (0.009)	−0.262*** (0.014)
Is_Race_2015	−0.142*** (0.009)	−0.236*** (0.014)
Is_Race_2016	−0.132*** (0.010)	−0.237*** (0.014)
Is_Race_2017	−0.140*** (0.010)	−0.235*** (0.014)
Is_Race_2018	−0.142*** (0.010)	−0.232*** (0.014)
Is_Race_2019	−0.148*** (0.010)	−0.256*** (0.014)
Is_Race_2020	−0.127*** (0.011)	−0.232*** (0.016)
Is_Race_2021	−0.155*** (0.010)	−0.232*** (0.015)
Is_Race_2022	−0.141*** (0.011)	−0.234*** (0.015)
Is_Race_Female_2009		0.275*** (0.019)
Is_Race_Female_2010		0.228*** (0.018)
Is_Race_Female_2011		0.232*** (0.019)
Is_Race_Female_2012		0.225*** (0.019)
Is_Race_Female_2013		0.256*** (0.019)
Is_Race_Female_2014		0.208*** (0.019)
Is_Race_Female_2015		0.176*** (0.019)
Is_Race_Female_2016		0.197*** (0.019)
Is_Race_Female_2017		0.178*** (0.019)
Is_Race_Female_2018		0.167*** (0.019)
Is_Race_Female_2019		0.201*** (0.020)
Is_Race_Female_2020		0.193*** (0.021)
Is_Race_Female_2021		0.145*** (0.021)
Is_Race_Female_2022		0.175*** (0.021)
Educ	0.153*** (0.0003)	0.153*** (0.0003)
Experience	0.090*** (0.0003)	0.090*** (0.0003)
Experience_Sqrd	−0.001*** (0.00001)	−0.001*** (0.00001)
Constant	−4,571,318.000 (3.04e7)	−4,024,120.000 (3.03e7)
Observations	1,090,039	1,090,039
Log Likelihood	−1,395,015.000	−1,394,206.000
Akaike Inf. Crit.	2,790,123.000	2,788,532.000
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01

Figure A9: Overall Female Wages: Single Females vs. Baseline Wage Gap

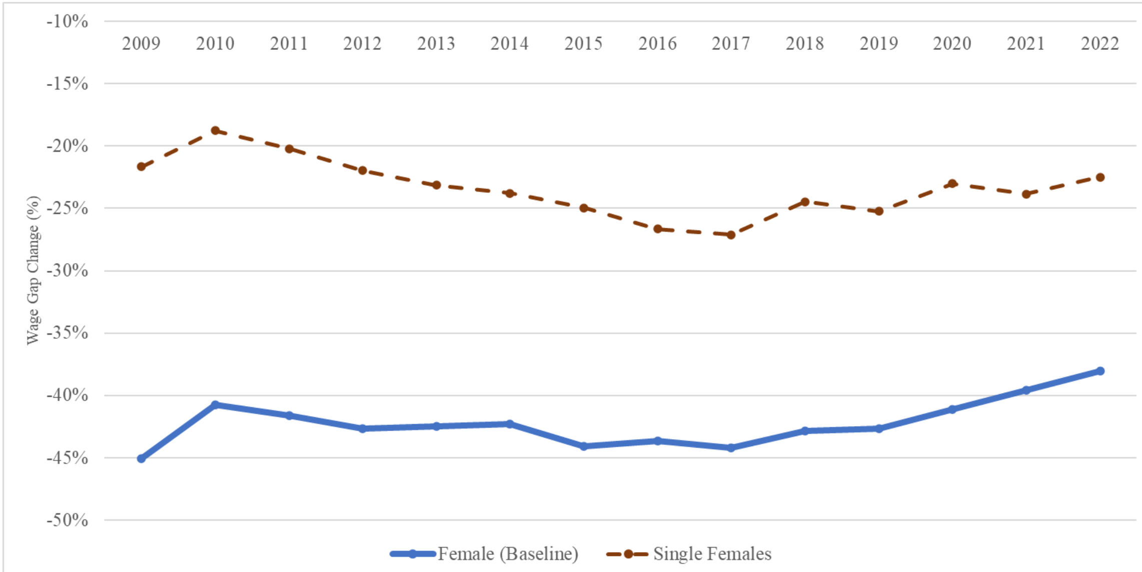

Figure A10: Married Female Wages

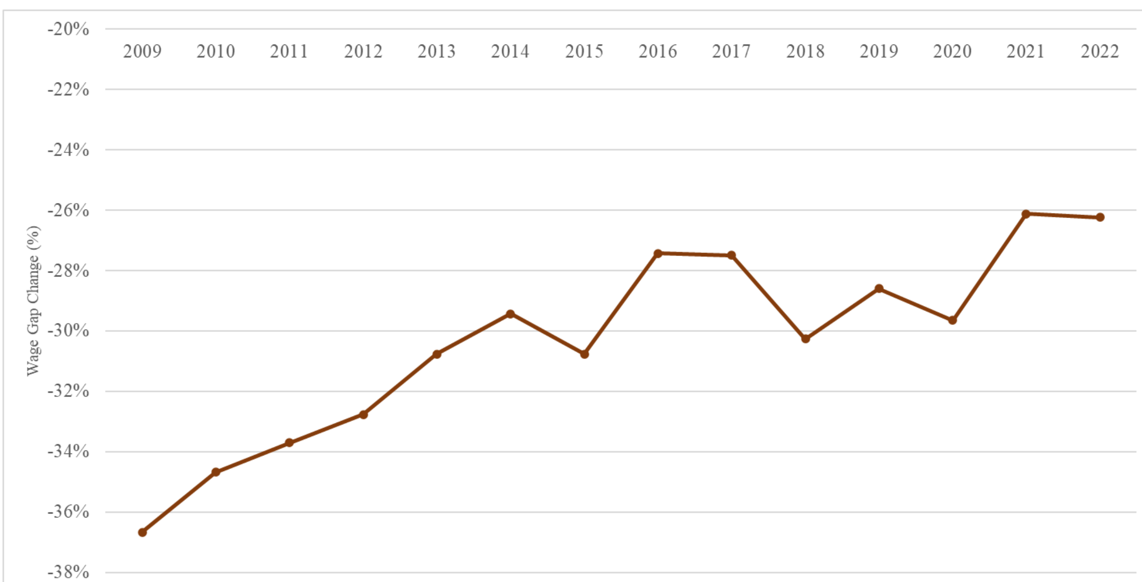

Table A8: Controlling for Married_Female vs. Baseline - Condensed

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_Female_2009	-0.439^{***} (0.006)	-0.217^{***} (0.009)
Is_Female_2010	-0.395^{***} (0.006)	-0.188^{***} (0.009)
Is_Female_2011	-0.403^{***} (0.006)	-0.202^{***} (0.009)
Is_Female_2012	-0.412^{***} (0.006)	-0.220^{***} (0.009)
Is_Female_2013	-0.412^{***} (0.006)	-0.231^{***} (0.009)
Is_Female_2014	-0.409^{***} (0.006)	-0.238^{***} (0.009)
Is_Female_2015	-0.428^{***} (0.006)	-0.250^{***} (0.009)
Is_Female_2016	-0.425^{***} (0.006)	-0.267^{***} (0.010)
Is_Female_2017	-0.431^{***} (0.006)	-0.271^{***} (0.010)
Is_Female_2018	-0.418^{***} (0.006)	-0.245^{***} (0.010)
Is_Female_2019	-0.417^{***} (0.006)	-0.252^{***} (0.010)
Is_Female_2020	-0.402^{***} (0.007)	-0.230^{***} (0.010)
Is_Female_2021	-0.386^{***} (0.007)	-0.238^{***} (0.010)
Is_Female_2022	-0.372^{***} (0.007)	-0.225^{***} (0.010)
Is_Married_Female_2009		-0.367^{***} (0.012)
Is_Married_Female_2010		-0.347^{***} (0.012)
Is_Married_Female_2011		-0.337^{***} (0.012)
Is_Married_Female_2012		-0.328^{***} (0.012)
Is_Married_Female_2013		-0.308^{***} (0.012)
Is_Married_Female_2014		-0.294^{***} (0.012)
Is_Married_Female_2015		-0.308^{***} (0.012)
Is_Married_Female_2016		-0.274^{***} (0.013)
Is_Married_Female_2017		-0.275^{***} (0.013)
Is_Married_Female_2018		-0.303^{***} (0.013)
Is_Married_Female_2019		-0.286^{***} (0.013)
Is_Married_Female_2020		-0.296^{***} (0.014)
Is_Married_Female_2021		-0.261^{***} (0.014)
Is_Married_Female_2022		-0.262^{***} (0.014)
Constant	7.493^{***} (0.008)	7.436^{***} (0.009)
Observations	1,090,039	1,090,039
R^2	0.290	0.296
Adjusted R^2	0.290	0.296
Residual Std. Error	0.866 (df = 1089993)	0.863 (df = 1089979)
F Statistic	$9{,}916.669^{***}$ (df = 45; 1089993)	$7{,}762.073^{***}$ (df = 59; 1089979)
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01

Table A9: Controlling for Married_Female vs. Baseline

	Dependent variable:	
	Log Wages	
	(1)	(2)
Is_2009	0.005 (0.008)	−0.038*** (0.010)
Is_2010	−0.068*** (0.008)	−0.103*** (0.010)
Is_2011	−0.097*** (0.008)	−0.129*** (0.010)
Is_2012	−0.091*** (0.008)	−0.118*** (0.010)
Is_2013	−0.085*** (0.008)	−0.105*** (0.010)
Is_2014	−0.075*** (0.008)	−0.090*** (0.010)
Is_2015	−0.025*** (0.008)	−0.044*** (0.010)
Is_2016	0.002 (0.009)	−0.006 (0.010)
Is_2017	0.025*** (0.009)	0.015 (0.010)
Is_2018	0.027*** (0.009)	0.011 (0.010)
Is_2019	0.056*** (0.009)	0.044*** (0.010)
Is_2020	0.070*** (0.009)	0.055*** (0.011)
Is_2021	−0.006 (0.009)	−0.008 (0.010)
Is_2022		
Is_Female_2009	−0.439*** (0.006)	−0.217*** (0.009)
Is_Female_2010	−0.395*** (0.006)	−0.188*** (0.009)
Is_Female_2011	−0.403*** (0.006)	−0.202*** (0.009)
Is_Female_2012	−0.412*** (0.006)	−0.220*** (0.009)
Is_Female_2013	−0.412*** (0.006)	−0.231*** (0.009)
Is_Female_2014	−0.409*** (0.006)	−0.238*** (0.009)
Is_Female_2015	−0.428*** (0.006)	−0.250*** (0.009)
Is_Female_2016	−0.425*** (0.006)	−0.267*** (0.010)
Is_Female_2017	−0.431*** (0.006)	−0.271*** (0.010)
Is_Female_2018	−0.418*** (0.006)	−0.245*** (0.010)
Is_Female_2019	−0.417*** (0.006)	−0.252*** (0.010)
Is_Female_2020	−0.402*** (0.007)	−0.230*** (0.010)
Is_Female_2021	−0.386*** (0.007)	−0.238*** (0.010)
Is_Female_2022	−0.372*** (0.007)	−0.225*** (0.010)
Is_Married_2009	0.176*** (0.006)	0.360*** (0.008)
Is_Married_2010	0.201*** (0.006)	0.375*** (0.008)
Is_Married_2011	0.206*** (0.006)	0.375*** (0.009)
Is_Married_2012	0.214*** (0.006)	0.379*** (0.009)
Is_Married_2013	0.207*** (0.006)	0.360*** (0.009)
Is_Married_2014	0.209*** (0.006)	0.355*** (0.009)
Is_Married_2015	0.189*** (0.006)	0.343*** (0.009)
Is_Married_2016	0.181*** (0.006)	0.318*** (0.009)
Is_Married_2017	0.173*** (0.006)	0.311*** (0.009)
Is_Married_2018	0.170*** (0.006)	0.321*** (0.009)
Is_Married_2019	0.164*** (0.006)	0.307*** (0.009)
Is_Married_2020	0.163*** (0.007)	0.311*** (0.010)
Is_Married_2021	0.187*** (0.007)	0.316*** (0.009)
Is_Married_2022	0.168*** (0.007)	0.297*** (0.010)
Is_Married_Female_2009		−0.367*** (0.012)
Is_Married_Female_2010		−0.347*** (0.012)
Is_Married_Female_2011		−0.337*** (0.012)
Is_Married_Female_2012		−0.328*** (0.012)
Is_Married_Female_2013		−0.308*** (0.012)
Is_Married_Female_2014		−0.294*** (0.012)
Is_Married_Female_2015		−0.308*** (0.012)
Is_Married_Female_2016		−0.274*** (0.013)
Is_Married_Female_2017		−0.275*** (0.013)
Is_Married_Female_2018		−0.303*** (0.013)
Is_Married_Female_2019		−0.286*** (0.013)
Is_Married_Female_2020		−0.296*** (0.014)
Is_Married_Female_2021		−0.261*** (0.014)
Is_Married_Female_2022		−0.262*** (0.014)
Educ	0.148*** (0.0003)	0.147*** (0.0003)
Experience	0.081*** (0.0003)	0.081*** (0.0003)
Experience_Sqrd	−0.001*** (0.00001)	−0.001*** (0.00001)
Is_Black	−0.097*** (0.003)	−0.105*** (0.003)
Constant	7.493*** (0.008)	7.436*** (0.009)
Observations	1,090,039	1,090,039
R^2	0.290	0.296
Adjusted R^2	0.290	0.296
Residual Std. Error	0.866 (df = 1089993)	0.863 (df = 1089979)
F Statistic	9,916.669*** (df = 45; 1089993)	7,762.073*** (df = 59; 1089979)
Signficance Levels		*p<0.1; **p<0.05; ***p<0.01