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The Effect Of An Increase in Minimum Wages on Gender

By

Prachee Arora

A Thesis is submitted in partial fulfillment of the requirements for the course Senior Seminar (EC 375), during the Spring Semester of 2019

While writing this thesis, I have not witnessed any wrongdoing, nor have I personally violated any conditions of the Skidmore College Honor Code.

Thesis Advisor: Monica Das

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Abstract

To estimate the effect of an increase in minimum wages on gender, this paper utilizes a natural experiment opportunity, arising from increases in 21 states of the U.S. and the District of Columbia in 2015. In my study, I implement a difference-in-differences (DID) methodology to evaluate the impact of the increase in minimum wages implemented in 2015 on gender in the *Production* industry, the *Arts, Design, Entertainment, Sports and Media* industry and the *Transportation and Material Moving* industry. Through my research, instead of focusing on the employment effects of minimum wages, I shed light on the effectiveness of minimum wages as a tool of redistribution of income for low wage earners. My results conclude that the greatest impact of an increase in minimum wages in 2015 can be witnessed in the *Production industry*, where earnings of single women with one child increased by 9.60 percent and earnings of divorced women with no child increased by 9.65 percent. My findings report that the second largest impact of an increase in minimum wages in 2015 was observed in the *Transportation and Material Moving* industry, where earnings of divorced men with one child increased by 6.80 percent and earnings of married men with no child increased by 6.69 percent. The impact of an increase in minimum wages in 2015 had no impact on the earnings of workers in the *Arts, Design, Entertainment, Sports and Media* industry.

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1 Introduction

The minimum wage has long been a contentious issue in the American consciousness, raising questions about its fairness, its effectiveness and as a tool of redistribution to lower wage earners. I will examine the effect of an increase in minimum wages and whether that affects men and women differently in the U.S.? This topic is extremely prevalent in the real world as minimum wages have the largest impact on employment figures and determine an individual's incentive to supply labor, which is equal to the number of participants in the labor force. Gender pay disparities vary across industries and as well as different job statuses within an occupation. These gender wage disparities originate not only from segregating women into certain industries and occupational levels, as a result depressing wages for workers in those industries but also arise from difference in work interruption between men and women.

Blau and Kahn (2000) state that traditionally, economic analysis of the gender pay and segregation across occupations has focused on gender-specific factors which often shed light on gender differences in qualifications or labor market treatment of similarly qualified individuals. Mohr (2014) in her article elucidates that men apply for a job when they meet only 60% of the qualifications, but women apply only if they meet 100% of the requirements. Women are victim to this statistic, as they don't feel confident until they've checked off every requirement on the list. Keaveny and Inderrieden (2000) state that job inputs as a determinant of fair pay have been considered primarily from an equity theory perspective. Equity theory is formulates the approach of comparing ratios of one's outcomes and inputs to a relevant equivalent. They argue that gender differences in job inputs may explain part of the gender differences in pay expectations. Women may have lower job inputs and often believe they actually deserve less. A number of theoretical models have examined the impact of minimum wages on employment figures. Studies on minimum wages by Lester (1946) focused on the effect of the introduction of federal minimum wage in the U.S. and other researchers such as Card (1992), Katz and Krueger (1994) have utilized natural experiment frameworks to evaluate minimum wage variations across states in the U.S.

A policy implication of an increase in minimum wage that affects men and women differently would be that it used to elevate the general well-being of the society to further increasing inequity between males and females. These differences across gender in job inputs may explain the wage differences in pay expectations between men and women. The main issue is the difference between the wages women receive and wages men receive but otherwise comparable in terms of relevant characteristics.

Through the course of this paper my aim is to examine the effect of an increase in minimum wages on gender in the U.S. in states that increased their minimum wages compared to states that did not alter their minimum wages in 2015 by exploiting the natural experiment opportunity. I will be implementing a difference-in-differences (DID) methodology to evaluate the impact of the increase in minimum wages implemented in 2015 on gender in the *Production* industry, the *Arts, Design, Entertainment, Sports and Media* industry and the *Transportation and Material Moving* industry. I hypothesis that an increase in minimum wages would affect men and women differently because gender segregation does play a crucial role in explaining why certain industries tend to be male dominated and in terms of explaining the inter-firm wage differentials. This differential impact of minimum wages on gender would exacerbate when there's an increase in minimum wages and suddenly employers are choosing to reduce earnings of female workers than male workers as a result. However, given that workers possess homogenous skills and qualifications at different occupational levels in the three industries, I expect income of women to increase significantly. Assuming that women tend to have lower pay expectations and as a result receive lower wages.

The paper contributes to the literature by analyzing the effects of an increase in minimum wages on gender. Instead of focusing on the employment effects of minimum wages, I examine the effectiveness of minimum wages as a tool of redistribution of income for low wage earners. As women tend to be at the lower end of the wage structure, minimum wages by asymmetrically increasing lower earning wages, could reduce the gender wage differential. Also, I inculcate demographic characteristics such as marital status and number of own children in the household to explain time periods of work disruption for men and women across the three industries I examine. My results do show that the effects of an increase in minimum wages across the three industries vary between men and women.

The paper is structured as follows: Section 2 reviews the previous literature on minimum wages and factors that may explain occupational segregation by gender; Section 3 discusses the data and variables used in my empirical analysis; Section 4 discusses the regression analysis and the expected signs for difference-in-differences estimators; Section 5 discusses the robustness checks conducted; Section 6 discusses cross-sectional regressions and includes findings on the impact of an increase in minimum wages on gender across the three industries; Section 7 and 8 conclude, provide suggestions for future research and discuss policy implications of the implementation of minimum wages.

2 Literature Review

Khamis (2013) states that the difference-in-differences analysis before and after the change in minimum wages is estimated for in treatment and control groups. The study acknowledges the main issue in the process of determination of treatment and control groups as the control group provides information in the absence of the treatment. Almost all research till data has focused on incorporating higher wage earners to account for the control group for minimum wage earners consistent with Acemoglu and Pischke (2003)'s study. This could be a viable control group but we would have to assume that minimum wages do not influence wage structures for higher occupation levels and income brackets above the minimum wage threshold. In my study, I exploit the natural experiment design, where some states implemented an increase in minimum wages and other states that did not in 2015 similar to Lester (1946)'s study to examine the effect of the establishment of the federal minimum wage in the U.S. The natural experiment approach does have an advantage over commonly used methodologies since treatment and control groups are identified by the exogenous variation in minimum wages. Whether states implemented an increase in minimum wages or not will determine which states will be a part of the treatment and the control groups.

Brülhart, Carrère and Trionfetti (2012) conduct a difference-in-differences estimation and their results conclude that trade liberalization after the fall of the Iron Curtain bolstered wages and total employment in Austrian border areas was three times larger compared to the effect on wages. However, wages are found to have adjusted more quickly than employment figures, which is consistent with the view that wages react more quickly to market conditions when compared to employment figures. Though labor-market histories and wages at the individual level were incorporated in their dataset, there was no information on demographic characteristics of Austrian workers. It could be possible that the occupational mix of workers in one area differed from that of workers in another geographical setting. These regional variations would be revealed if occupational mix was controlled for and indicated disparities between wages of men and women.

Leigh (2003) also conducts a quasi-experiment to evaluate the impact of a rise in minimum wages on employment arising from six increases in Western Australia during the period 1994 – 2001. Though he accounted for changes in employment-to-populations in treatment and control groups, he does not incorporate sufficient statistical controls in his regression analysis. He does not include any other controls such as occupation levels across industries or age of the workers. Also, Leigh does not include or control for employment trends before and after between the treatment and control groups. Employment trends would report whether or not there are similar divergence trends between the treatment and control groups. However, he does conduct a falsification test to test if any of the six time periods dominated his results. In my study, I will examine the impact of an increase in minimum wages and how that affects the income of men and women. An individual's employment status can vary between full-time and part-time employment and necessarily does not provide information on how income is redistributed among lower wage earners. The majority of the existing literature focuses on the employment effects of minimum wages but does not explain the mechanism through which gender wage disparities at varying occupational levels can be reduced across industries.

Pereira (2003) evaluates the employment effects of an increase in minimum wages for workers aged 18 and 19 in Portugal since the Portuguese minimum wage amendment was directly targeted at teenagers. It's intriguing how she can examine the intended effect on teenagers' employment rates and expand prevalent literature on employment effects of minimum wages that have been a source of controversy. Stewart (2004)'s study examined employment shifts of those directly affected by an increase in minimum wages with those with higher earnings. However, it's difficult to correctly identify which subgroup of ages is the intended target of an increase in minimum wages. Therefore, I will include all subgroups of ages in my dataset and will be incorporating the age variable to capture the demographic characteristics of male and female workers.

The main explanations in the variation in the gender wage gap in the U.S are elucidated by gender segregation across occupations with varying rents and returns and gender differences in human capital accumulated. Bergmann (1974)'s overcrowding model formulated that discriminatory exclusion of women from "male dominated" jobs would result in an excess supply of labor in "female dominated" occupations, further depressing wages in these occupation. However, the role of the gender of the employer might play a significant role assuming that an employer might choose to discriminate against a particular gender and not formulate rational employment decisions on the basis of an individual's pre-market characteristics. Conventionally, in most occupations women tend to be an intended target of occupational segregation.

Mincer and Polachek (1974) estimated the earnings functions with relation to wages to investments in schooling for measuring the impact of work experience on gender wage differentials. They try to capture the extent to which the gender wage gap is a consequence of discrimination by employers. They draw these comparisons by controlling for factors that reflect differences in human capital between men and women. Gender wage differentials that remain unexplained after controlling for varying proxies of experience and productivity in their model are interpreted as labor market discrimination. However, Bielby and Baron (1986) argue that human capital model does not account for occupational segregation on the basis of gender but it could explain why men and women end up working in different industries or in contrasting occupational titles in an organization. It could be argued that if there are worker characteristics that are unobserved my firms and if women tend to have a lower supply of such characteristics then the "unexplained" aspect of the model would overestimate the presence of discrimination.

Blau and Kahn (2000) suggest that if certain job titles have barriers to entry then this would restrict women from entering certain occupations and this could underestimate the existence of discrimination. They also argue that women employed in certain fields and occupations require comparatively less accumulation of human capital and on-job training and as a result earn lower wages. In addition, Hashimoto (1982) elucidates that opportunities for on-job training, which is offered to workers formally or informally are believed to be an important fringe benefit existent across most occupations. His findings on the employment effects of minimum ages report that lost employment often deprive unemployed workers of access to greater job inputs and training. He also states that even workers who manage to remain employed at wages near the minimum wage may experience a reduction in training as well. This would reduce access to labor market experience for women assuming that the majority of the workers at the receiving end of these negative employment impacts are women. It would be rational to argue that because women have acquired less human capital compared to male counterparts in rigorous industries, they as a result are more likely to receive fewer fringe benefits and lower wages.

Varca (1983) argues that sex differences in job satisfaction revolve around organizational rewards and that these differences are moderated by occupational level. It appears that men employed at upper occupational levels and women employed at lower occupational levels are more satisfied with their job and pay satisfaction. This could be precisely why lower level women reported relatively high pay satisfaction while receiving the smallest salaries is unclear. Though women employed at lower occupational levels might have reported high pay satisfaction while receiving the smallest salaries but it could also be argued that providing higher fringe benefits could offset their lower wages. Leaving lower level women more satisfied with their low wage earnings.

Black et al. (2004)'s findings conclude that well-educated college women in the U.S earn approximately thirty percent less than their non-Hispanic white male equivalents. Their methodology highly relies on the measures for the role of labor market experience and majors pursued by individuals in college. However, it could also be true that their analysis isn't doing justice to individuals that are choosing to further invest in higher education. Not all college majors require time to be invested in labor market experiences and sometimes individuals who choose to pursue higher education instead are making a practical choice. Majors in fields such as health care, legal & criminal justice and academia do not require labor market experience but expertise and further specialization in these fields is a fundamental requirement. Their findings would be more convincing if a higher percentage of individuals that seek labor market experience tend to be men when compared to women across different occupations.

Though a major pursued in college can determine wage disparities across occupations, it could be argued that it isn't a definite indicator of an industry or the type of job an individual will choose to work in that particular field of study or outside of it. The labor market experience, which is deemed important for recent college graduates but only involves rudimentary tasks at the entry level, isn't a fair judgment of one's capabilities and peak career trends and earnings. Their methodology of incorporating a data set that focuses only on college graduates is a rational choice because it can be argued that college graduates who are being accepted for entry-level positions on an average are earning wages close to the minimum wage. Considering that these individuals are recent college graduates and have not invested a significant amount of the time in acquiring the labor market experience, they would relatively earn lower wages. Gender wage disparities across occupations can be formulated on the basis of an individual's field of study in college but it surely isn't an ideal predictor. If discriminatory exclusion of men and women from certain occupations is evident, this could depress wages in occupations where equally qualified, productive and efficient workers are employed. Blau and Ferber (1991) also argue that because women intend to spend a substantial amount of time out of the labor market, they are willing to accept lower rewards for experience in return for lower depreciation rates during periods of work interruption.

Alkary and Tower (2006) explain that differences between women and men have traditionally been attributed to the limited number of women in the higher earning levels of organizations. Women are often concentrated in lower occupational statuses because of limited initial hiring at the entry level and a lack of upward mobility within organizations. Concentration of women in lower-level positions often means segregation in lower-paying positions. As a result, gender typing tends to result in segregation of women in certain positions and fields. Upward mobility within organizations may combat gender segregation, resulting in the progress of women into upper-level and higher earnings position. However, Banerjee and Newman (1993) conclude many organizational and sociocultural factors deny women the benefits of upward mobility. They also argued that a greater proportion of women compared to men were handicapped while advancing their career and received lower wages than their male equivalents.

Tying into that Blau and Kahn (1992) analyze the paradoxical nature of the wage structure in the U.S. when compared to wage structure in other countries across the world. If educational attainment is the primary source of explaining the differential impact of wages on gender, then this raises the question that why are women in the U.S. that are highly educated when compared to women in other countries and still experience the largest inequality in wages? The U.S. has also had a longer and stronger commitment to antidiscrimination laws than most economically advanced nations, the U.S. has traditionally been among the countries with the largest gender gaps. The striking finding of their study is that the higher the level of inequality in the U.S works to increase the gender differential in the U.S relative to all the other countries in the same and fully accounts for the lower gender earnings ratio in the U.S. compared to the Scandinavian countries and Australia (the countries with the smallest gaps).

Goldin and Katz (2007) argue that research using large representative data sets, such as the Current Population Survey (CPS) or data from IPUMS (U.S, Census data), shows that the human capital model explains very little of the observed wage differentials between men and women. They also state that large data sets such as the CPS and IPUMS typically lack sufficient detail on relevant human capital variables. These data sources typically have no data on years of work experience and have only rudimentary information on number of years of schooling. In the absence of adequate measures of premarket human capital characteristics, researchers can use industry and occupation indicators as proxies for market skills. Although, this approach complicates the interpretation of the gender wage gap if industry and occupation assignments are themselves the consequence of labor market discrimination. Pal and Waldfogel (2016) analyzed data from the Current Population Study (CPS) to examine the trends in family wage gaps, but they did not analyze differences across demographic characteristics across wage distributions. However, these large datasets offer the ability to control for demographic characteristics at the individual level that determine earnings.

Several studies have adopted different regression models and made use of different datasets covering varying time periods. Although there is, considerable variability in inferences regarding gender wage gaps but there are also some generalizations that can be accepted. The gender wage differential in several studies often remains unexplained even after carefully conditioning on pre-labor market skill differences such as occupation and labor market experience—that could itself be a result of discrimination experienced while employed in the labor market. If one argues that occupational segregation is not a result of discrimination as a presumption, there is existing evidence on gender wage disparities. Pay disparities are often attributed to the segregation of women in certain “female-dominated” occupational levels and industries.

Anderson et al. (2003) in their findings conclude that women pay a wage penalty for motherhood, whereas men on the other hand earn a wage premium for fatherhood. Motherhood leads to women undertaking more responsibilities for childcare, which leads to reduced time to be invested in the labor force. Kmec (2011)’s study examined the difference between mothers’ and childless women’s motivation to work and work effort because of the traditional responsibilities undertaken by women. However, she found no difference between mothers’ and childless women’s willingness to work, work intensity and effort. Contrastingly, Azmat and Ferrer (2017) found that the prevalence of children reduces women’s on job performance and mothers often can be looked upon as being less committed and competitive. This may lead to employers consciously or unintentionally discriminating against mothers and these perspectives of the employers may lead to biases in hiring and work compensation decisions. As a result, this may lead to reduced upper-mobility and lower promotional outcomes for women. A substantial portion of the gender wage differential can be assigned to different effects of parenthood on the division of labor by gender. In my study, it is important to take demographic characteristics on the individual level into account to evaluate the variation in income that might lead to parenthood penalties and premiums for women and men due to an increase in minimum wages. Inequalities across women by comparing different marital statuses would better indicate women’s personal characteristics that may influence their occupational statuses.

Budig and Hodges (2010) explored variation in the wages association with the “motherhood penalty” and their findings conclude that the penalty associated with motherhood is larger for women at the lower end of the wage structure. The presence or number of children estimates the measure of “motherhood penalty” in my model, which is a proxy for work disruption. This “motherhood penalty” at the bottom end of the wage distribution in my model would be interpreted in a way that if the impact of an increase in minimum wages has the greatest influence on the income of married women, my results would indicate wage disparities among women as well. A major limitation of their study is that they cannot examine the intervening mechanisms or the simultaneous varying effects on men and women over a time period. Through my study, I fill this gap in the literature by examining the effect of an increase in minimum wages on men and women with different marital statuses and the number of their own children across three different industries.

3 Analytical Framework

To investigate the effect of this public policy of an increase in minimum wages I obtained my dataset from IPUMS-CPS, which consolidates data from the Current Population Survey (CPS). The CPS is a monthly U.S. household survey that is conducted by the U.S. Census Bureau and the Bureau of Labor Statistics. The dataset I acquired from IPUMS-CPS is microdata that provides specific information about individuals and households. This dataset is not constant across time, as same individuals and households in all the 50 states in the U.S. were not surveyed over a period of time. To examine the impact of an increase in minimum wages across time it would be advantageous to survey the same households but that's an aspect of my dataset that I cannot control for. On the other hand, this could also work in favor of avoiding any selection bias inculcated in my data set by cherry picking individuals or households to be surveyed in a given state. Since I want to examine the effect on an increase in minimum wages implemented by states in the U.S. in 2016 and how that effects men and women differently, the variables harmonized in IPUMS-CPS make it approachable for me to capture the effect spatially. In January of 2015, 21 states of the U.S. and the District of Columbia increased their minimum wages. The *treatment* states and *control* states are reported in Table 1.

Incwage. This variable measures the annual wage and salary income for men and women in dollars. Freeman (1996) elucidates that the ultimate result of amendments in the minimum wages isn't captured by its unintentional consequences on the employment figures but on the effectiveness of minimum wages to serve as a tool of redistribution to decrease inequity within our society. Given the best scenario, the effective implementation of minimum wages would will allocate the earnings distribution towards the lower wage earners. Mincer (1974) evaluates the rates of return to education using the Mincerian earnings equation, where the dependent variable is the logarithm of wages or earnings and the explanatory variables include distinguished demographic characteristics such as number of years of schooling, sex, work experience etc. I include this variable to better account for the earning gains delivered by an increase in minimum wages for workers by accounting for several demographic characteristics.

Sex. This variable is each individual's gender. Anker (1997) states that historical literature on occupation segregation is not concerned with occupational segregation per se, but its impact on gender wage differentials. Given the differences in acquired labor market skills accounts for a substantial element of the gender wage disparity. If wages vary on the basis on gender orientation, this disparity would result in women receiving inferior pay. This variable would indicate the displacement of incwage between men and women in $treatment_i$ states after the increase in minimum wages in 2015.

Educ. This variable denotes the highest educational attainment of an individual, which is measured as the highest number of years at the school or college level. Mincer (1974) interprets the coefficient of education in the log wage regression as the main source of elevating productivity assuming that wages must only be proportional to productivity, by accounting for attributes observed by firms across industries. I'm assuming that there aren't attributes proportional to productivity that are not accounted by firms incorporated in the Mincerian wage equation.

Age. This variable provides information about an individual's age at their last birthday. Mihăilă (2016) states that the gender wage gap remains inconsequential when employees are inexperienced and it enlarges with age. She elucidates that on the other hand gender wage gap for employees who work full time without any labor market disruptions declines with age. I will be dropping ages lower than 16 years old because the legal minimum wage to work full-time in the U.S is 16. My dataset includes information on the different ages at varying occupation levels across industries at a given point in time and it does not provide information on how employment for individuals varies across age. I use $agedummy_t$ to differentiate between individuals that will be a part of the labor market and those that will not be. Individuals younger than and equal to 66 years of age will receive the code 1 and individuals older than 66 years of age will receive the code 0. I choose 66 years of age as a determinant whether an individual will receive code 1 or 0 because the full retirement age in the U.S. is 66 years. It's important to create this variable because different occupation levels in different industries have diverging peak earning years. I'm including a wide range of ages in my dataset because the emphasis on the peak earning years across industries is not within the scope of this paper.

Industry. This variable states the type of industry in which an individual performed her primary occupation. This variable provides information on the type of work setting or sector and the occupation variable states an individual's specific job responsibilities and functions. Gosling (1996) concludes that minimum wages would reduce income inequality amongst working families, as many low income earners are either single or have spouses that are low incomers. By incorporating this variable I could precisely examine the impact of an increase in minimum wages in industries that are dominated by working families such as the *production* or *transportation* industry.

Marst. This variable gives each individual's current marital status and states whether their spouse is currently living in the same household. The majority of the individuals in my dataset are single (never married), divorced or married with their spouse currently living in the same household. Waldfogel (1998) elucidates that though gender differentials may have narrowed down both in the U.S and Great Britain, a substantial wage gap is prevalent between women with children and women without children. Although, he controlled for labor market experience and eradicated the wage effects of children, the unexplained impact of children remained. I do consider the effects of marriage on earnings as they may differ from the effects of children on earnings. To study the impact of minimum wages on one's marital status I generate the $marstdummy_i$ variable to provide information on an individual's marital status. Polachek (2004) argued that though wage disparities between men and women are trivial, wage disparities between men and married women have remained substantially significant. I will be focusing on individuals that are single (never married), divorced and married. Individuals that are single (never married) will receive the code 6, divorced individuals will receive the code 4 and married individuals will receive the code 1 based of the codes IPUMS-CPS has employed.

Nchild. This variable is the number of own children in the household. I'll be manipulating this variable in a way to account for time outside the labor market or time off school depending for women depending on the number of own children. Michael and Lazear (1971) argue that the number and age composition of her children may affect a woman's wage. The presence of young children increase's the wife's time demanded at home and reduces her availability to participate in the labor force. Gangl and Ziefle (2009) argue that because childbirth often necessitates mothers' absolute withdrawal from the labor force for extended periods of time, the incidence of the costs associated with work interruption typically fall on mothers. One can also assume that the marital status and the presence of children is a crucial factor since the geographical factor is and her access to labor market exposure is likely to be influenced and often bound by the location of her husband's job placement. I hypothesize that this would directly impact the annual and wage earnings that married women would earn on the basis of accumulated work experience. Sutter and Miller (1973) elucidate that the lifetime accumulated work experience between single and married women explain the difference between their median incomes. Their results conclude that the difference in the median income for women with varying martial statuses reduces as the gap between the lifetime work experience narrows. The remaining difference between single and married women was explained by examining who worked each year, as married women would be more likely to work part time for years when they're expecting an offspring or looking after one.

I incorporate $nchilddummy_i$ to know the number of own children in the household. This would help me provide information about the number of times women had to take time out off the labor market or off school based on the number of their own children. Also, because work experience required for occupation levels isn't constant across industries. It will be more realistic to account for the disruption in the labor market or time taken off school for women and examine if this puts them at a disadvantage. Individuals will receive values 0, 1, 2, 3, 4, 5, 6, 7, 8 and 9 based on the number of their own children in the household.

Occ2010. This variable provides information based on the occupation levels of individuals in different industries. These occupation levels are coded based on the Central Bureau's 2010 occupation classification procedure. Card, Cardoso and Kline (2016) elucidate that there are massive earnings differential across various firms and establishments that sort employees into high and low establishments contributes to inequality in earnings in the U.S as men are more likely to work in higher paying firms and capture a greater portion of the establishment premium than women. I include all occupation levels in the *Production* industry, the *Arts, Design, Entertainment, Sports and Media* industry and the *Transportation and Material Moving* industry. The *occ2010* variable in IPUMS-CPS codes all occupation levels in each industry category. I focused on the impact of an increase in minimum wage on workers in these industries, as workers in this industry are a homogenous group of individuals undertaking comparatively similar job responsibilities and functions. Hakim (2006) elucidates that in several occupations, the highest recognition and accomplishment requires consistent dedication and extensive effort and artistic work of all kinds is one such example. Individuals whose artistic output is uncertain and infrequent are less likely to be in greater demand when compared to those with a competitive, appreciable and persistent output. Part-time workers in such fields cannot be excluded but it would be unlikely for them to acquire enormous appreciation for their work.

Treatment groups. This variable incorporates the 21 states of the U.S. and the District of Columbia that increased their minimum wages in 2015. The treatment groups will capture the effect of an increase in minimum wages in states that increased their minimum wages compared to states that did not across time. Meyer (1995) states that treatment groups captures the causal effect of the treatment on the outcome of interest for unit i and period t and the treatment group can usually be defined by the variation in another variable such as the variation in minimum wages.

Control groups. The variable includes the states of the U.S. that did not alter their minimum wages in 2015. The minimum wages in these states will remain the same before and after 2015. The control groups are comparison groups over the same time period as the before and after groups that have similar characteristics as the treatment groups. The only difference is that these groups are untreated groups when compared to the treatment groups. The difference-in-differences estimation to serve its true purpose expects intervention in treatment groups need to be unrelated with the outcome of interest and necessitates no spillover effects of the treatment groups in control groups.

Table 2 reports the descriptive statistics for the general difference-in-differences population regression function.

4 Regression Analysis

I use multivariate regressions to explain the effect of an increase in minimum wages and how that affects gender differently. The following Equation 1 denotes my regression model. Using the difference-in-differences methodology, I will be evaluating the effect of an increase in minimum wages in states that increased their minimum wages compared to states that did not alter their minimum wages in 2015. The dependent variable is the $incwage_i$ that men and women earn in different industries and at diverse occupation levels. I will be using an alternative form, which has the log on the left-hand side of the equation. The interpretation of this variable is that if $treatment_i$ changes by 1 unit, then $incwage_i$ would change in percentage values. $Incwage_i$ would change by β_1*100 percent, keeping $yeardummy_t$ and $interaction_{it}$ constant for event unit that *treatment* increases. The first explanatory variable is the $treatment_t$ and states that increased their minimum wages in 2015 will be part of the *treatment group*. States that did not alter their minimum wages in 2015 will be part of the *control group*. States that are part of the *treatment group* will be defined as $treatment_t$==1 on the basis of their state (FIPS code). States that are part of the *control group* will be defined as $treatment_t$==0 on the basis of their state (FIPS code) as well.

The second explanatory variable is the $yeardummy_t$ variable, which is a time dummy. The $yeardummy_t$ takes the value 0 for years 2013 and 2014 that are years before the increase in minimum wages was implemented. For years 2015, 2016 and 2017, I generated $yeardummy_t$==1 because the increase in the minimum wages in $treatment_t$ states took place in January 2015. This would be the time period in which the effect of an increase in minimum wages on men and women would be observed in *treatment groups* when compared to no changes in the *control groups*. The $interaction_{it}$ is equal to the product of the $treatment_t$ and the $yeardummy_t$, which would capture the heterogeneous effects of an increase in minimum wages during 2015, 2016 and 2017 on men and women. I generated male==1 and female==0.

$$\ln(\text{incwage}_{it}) = \alpha + \beta_{1*}\,\text{treatment}_i + \beta_{2*}\,\text{yeardummy}_t + \beta_{3*}\,\text{interaction}_{it} + \epsilon_{it} \quad (1)$$

I expect the sign of the coefficient of the $treatment_i$ to be positive across all the 3 industries because that would reflect a positive relationship between an increase in minimum wages in *treatment groups* and the $incwage_i$. I hypothesize the sign of the coefficient of the $yeardummy_t$ to be positive for all the 3 industries as well because that would explain that after an increase in minimum wages that took place in 2015, the $incwage_i$ would also increase. Also, I hypothesize the sign of the coefficient of the $interaction_{\mathrm{it}}$ to be positive because the difference-in-differences analysis would evaluate the difference in *treatment groups* before and after the increase in minimum wages, the difference in *control groups* before and after and then take a difference of the two. Brülhart, Carrère and Trionfetti (2012)'s result elucidate that the estimate coefficient for the interaction term evaluates whether and how the dependent variable progressed differently in the treatment groups compared to control groups after the fall of the Iron Curtain in 1990. A positive sign would indicate the effectiveness of an increase in minimum wages in *treatment groups* compared to *control groups* in 2015. I do expect the $interaction_{\mathrm{it}}$ coefficient to be a high positive value for women when compared to men and anticipate even a higher value for married women when compared to married men. It would be rational to argue that women with household necessities and responsibilities tend to accumulate less labor market capital when compared to men and have less time to invest in job-specific training. As a result, do not land up in higher-earning occupational levels and are over-represented in lower-earning jobs in labor markets. Weichselbaumer and Winter-Ebmer (2005)'s results from their meta-analysis of 263 international gender wage gap studies conclude that during the 1990s women earned on average 26 percent less than men. I hypothesize the $interaction_{\mathrm{it}}$ coefficient to be a high positive figure for married women with children when compared to married men with children across different industries and expect a higher positive value for divorced women as their own number of children increase. This would explain that parenthood advantages that are existent for men across industries, where as married women employed with similar human capital characteristics earn significantly less. Therefore, minimum wage impacts on the lower bottom end of the wage distribution are the greatest. The ϵ_{it} term is the stochastic error term in my model.

5 Robustness Checks

Though the majority of the results reported in Tables 6 through 23 are significant, this does not imply that they are robust. I utilize the Annual Social and Economic Supplement Weight (ASECWT) incorporated in my dataset obtained from IPUMS-CPS to correct for heteroscedasticity by adjusting the individuals weights in the sample. Tables 24 though 41 include the robust results testing for heteroscedasticity for men and women at different marital statuses and number of children. My results prior to correcting for heteroscedasticity indicate that my results were driven by analytical weights inflation. Tables 42 through 59 summarize the VIFs for all the explanatory variables in my final model and because the values of the VIFS for each explanatory variable are less than 5, I can conclude that there is no multicollinearity between the explanatory variables in my model.

6 Results

Tables 3, 4 and 5 report results from the log-linear regression for the impact on $incwage_i$ for single men and women in the *Production* industry, *Arts, Design, Entertainment, Sports and Media* industry and the *Transportation and Material Moving* industry at different occupational levels in $treatment_i$ states. As shown in Table 3, the sign for the $treatment_i$ variable, which indicates the states that increased their minimum wage, is negative. Therefore, a 1 unit change in the $treatment_i$ coefficient decreases the $incwage_i$ in percent values. This is not a sign I expected for the $treatment_i$ variable; respectively I expected $incwage_i$ of married and divorced women with children to increase the most. However, my results conclude that single women with one child and married women with one child, experienced the greatest decline in $incwage_i$ in $treatment_i$ states. A 1 unit change in the $treatment_i$ coefficient, decreased $incwage_i$ of single women with one child by 6.38 percent and married women with one child by 6.24 percent in the *Production* industry, significant at 1 percent level. This could be interpreted in the way that decreases in $incwage_i$ of single women with one child and married women with one child in *treatment* states could be redistributed to single men with no child and divorced men with one child as they experience the smallest decrease in $incwage_i$. The $yeardummy_t$ variable indicates that the greatest increase in $incwage_i$ in 2015 is observed for single men with one child and married women with one child. A 1 unit change in the $yeardummy_t$ coefficient increased $incwage_i$ for single men with one child and married women with one child by 4.32 percent, significant at 1 percent level. It's intriguing how my results for single men and married women with one child are affected similarly given the significant difference in marital statuses between the two. My results for the $interaction_{it}$ variable conclude that the largest impact of an increase in minimum wages in 2015 is on single women with one child and divorced women with one child. A 1 unit change in the $interaction_{it}$ coefficient increased $incwage_i$ of single women with one child by 9.60 percent and divorced women with no child by 9.56 percent, significant at 1 percent level. The findings for divorced women with one child are consistent with the findings of Greene and Quester (1982) that conclude that wives employed in the labor market as a buffer against marital failure should be more interested than other wives in on-job training.

The results for the *Arts, Design, Entertainment, Sports and Media* industry are concluded in Table 4. Although, these results are positive insignificant I do observe an expected sign for the $treatment_i$ variable. My results conclude that $incwage_i$ of divorced women with one child and single men with one child were the ones that were most affected. A 1 unit change in the $treatment_i$ coefficient increased $incwage_i$ of divorced women with one child and single men with one child by 2.20 and 1.97 percent. The results for divorced women with one child are consistent with the literature on the wage penalty associated with motherhood. This price associated with being a mother that fathers don't experience will impact the majority of women and exacerbate gender wage inequality. For divorced and single mothers, the penalty of motherhood could contribute to the gap in earnings of households run by a single women and households headed by a man. The $yeardummy_t$ variable has the greatest impact on the $incwage_i$ of married men with no child and single men with no child. A 1 unit change in the $yeardummy_t$ coefficient increased $incwage_i$ of married men with no child by 1.95 percent and single men with no child by 1.94 percent, significant at 1 percent level. These findings are consistent with the literature on marital wage premium for men indicating that causation might run from marriage to earnings. My results for the $interaction_{it}$ variable conclude that the implementation of an increase in minimum wages in 2015 had no impact on gender in the *Arts, Design, Entertainment, Sports and Media* industry. Though these results are negative insignificant, the largest impact of an increase in minimum wages in 2015 is on single men with one child and divorced men with one child. A 1 unit change in the $interaction_{it}$ coefficient decreased $incwage_i$ of single men with one child by 9.86 percent and divorced men with one child by 9.38 percent. These results are consistent with the findings of Dex, Sutherland and Joshi (2000). They conclude that the wage of worst paid men fell to meet the wages of the lower earnings of women, rather than the latter experiencing a positive advancement.

The results for the *Transportation and Material Moving* industry are concluded in Table 5. For the $treatment_i$ variable I do not observe an expected sign. The $treatment_i$ variable substantially decreased $incwage_i$ of divorced men with one child and married men with one child. A 1 unit change in the $treatment_i$ coefficient decreased $incwage_i$ of divorced men with one child by 9.09 percent and married men with one child by 8.99 percent, significant at 1 percent level. Hill (1979) concludes that married men have higher wages than divorced or separated men, who have higher average wages for single or non-married men. This decrease in $incwage_i$ of married men in $treatment_i$ states would be justified as a decrease in their earnings would be allocated to higher earnings for divorced women with one child as divorced women with one child have the smallest decrease in $incwage_i$ in the $treatment_i$ states. The $yeardummy_t$ variable has the greatest influence on the $incwage_i$ of single women with no child and divorced men with one child. A 1 unit change in the $yeardummy_t$ coefficient increased $incwage_i$ of single women with no child and divorced men with one child by 7.91 percent, significant at 1 percent level. The $interaction_{it}$ variable indicates that an increase in minimum wages in 2015 is on $incwage_i$ of divorced men with one child and married men with one child. A 1 unit change in the $interaction_{it}$ coefficient increased $incwage_i$ of divorced men with one child by 6.80 percent and married men with one child by 6.69 percent, significant at 5 percent level. The findings for married men are consistent with Kenny (1983)'s study which explains that the marriage wage premium is a result of return for the higher human capital accumulation that married men make by working longer hours and gaining more labor market experience.

Given that the R-squared values for all my models are between 0.2 – 0.4 %, this indicates the variation in $incwage_i$ that the independent variables explain collectively is low. I tabulated sex based on the varying occupational levels for the *Production* industry, *Arts, Design, Entertainment, Sports and Media* industry and the *Transportation and*

Material Moving industry to know more about the number of observations across industries and their gender breakdown. In the *Production* industry, there were 25, 532 observations and out of which 17,913 were men and 7,619 were women. In the *Arts, Design, Entertainment, Sports and Media* industry, there were only 9,089 observations and out of which 4,668 were men and 4,421 were women. In the *Transportation and Material Moving* industry, the total number of observations are 29,185 and out of which 24,268 were men and 4,917 were women. These number of observations for men and women across industries would further decrease in number when accounting for different marital statuses, number of own children in the household and the age. This could also be the rationale for the R-squared being so low. However, previous quasi-experiments modeled by Leigh (2003) and Reeves et al. (2017) have also reported low values of R-squared.

7 Discussion of Results

Admittedly, there are a number of limitations in my study. In examining the effect of an increase in minimum wages on gender in 2015, my study only incorporates horizontal segregation across industries. The dataset I obtain from IPUMS-CPS lacks information on the hierarchical rankings of different occupational levels in different industries. The undisrupted full-time labor force participation of women when compared to men is not the only issue in the gender wage disparity. Hakim (1979) states that both horizontal segregation and vertical segregation exacerbate women's lower earnings. I could have accounted for this problem if hierarchical rankings for different occupational levels across industries were incorporated in my dataset. Another limitation of my study is that I do not focus on a specific subgroup of age. I include individuals in my dataset that meet the age requirement to legally work full time in the U.S or are of an age less than the retirement age. As I reviewed the existing literature on the effect of age on wages and productivity it was difficult for me to establish how age solely would influence labor market productivity given that productivity is highly individualistic and also occupation and industry specific. To establish this relationship between age and productivity I would need to acquire data from the worker-firm matched data. Although, the increase in the minimum wage was not aimed directly at a specific subgroup of age it would be intriguing to further evaluate which subgroup of age is driving my results. This would also explain how employment elasticities play a role depending on the context in which increase minimum wages are implemented. Card, Cardoso and Kline (2016) state that if women have a less elastic job mobility arrangement with reference to wages and have a flatter earnings profile than men then gender wage disparities across employers may intensify.

Another limitation is that there could be measurement errors inculcated in my dataset. During 2013-2017, which is the time period of my study, there could have been changes in descriptions or variations in survey methods that may bring out discrepancies in the studied variables. To add on to the validity of my results, it is necessary for me to include average full-time and part-time employment trends for men and women or number of hours worked at every occupation level before and after in treatment and control states. This would conclude whether the preferences or incentives for individuals regarding the number of hours they choose to work and if trends in average full-time and part-time employment for men and women across industries changed after an increase in minimum wages in 2015. I also do not account for different $interaction_{it}$ variables for different *treatment* states to account for the divergence in the effect of the $treatment_i$ that may differ across geographical locations.

As my study only focused on the effect of a rise in the minimum wages on gender in 2015, there are several possible extensions of my paper. A basic extension of this paper is to evaluate the costs associated with raising the minimum wage against the higher earnings redistributed to lower wage earners. This requires learning more about workers who are earning the minimum wage and how household income is affected by minimum wage increases. Another potential extension of this paper is to examine the effect of an increase in minimum wages and the impact it has on public health and goods provision across states similarly to Leigh, Leigh and Du (2018)'s study. In my study because I include a wide range of ages it would be intriguing to examine if firms across industries alter the age structure of their organizations' workforce as a result of an increase in the cost of employing entry-level workers? Simon and Kaestner (2004) estimate the effect of minimum wages on the provision of employer health insurance and pension coverage. Their analysis also investigates compensating gender wage differentials for fringe benefits. Another potential aspect is to explore how women's representation in higher-earning positions and powerful roles affect the gender wage gap. Hirsch (2013) by utilizing employer-employee data concludes that women's representation in upper-level German management positions reduces the gender wage gap. Stainback et al. (2016)'s findings conclude that women's access to upper-level management positions is likely to reduce gendered biases and inequalities. Another way of examining the impact of an increase in minimum wage on gender would be through studying the breakdown of what percent of the payroll taxes by men and women are allocated in funding social security every month.

One other extension is to further examine the effect of minimum wages and the impact it has on gender in emerging economies. It could be argued that larger effects of minimum wages are hypothesized in emerging economies as minimum wages are often set at a higher level or because a larger percentage of the workforce is unskilled and are earning wages near the minimum wage. However, the implementation of minimum wages in emerging economies might be challenging to enforce due to the existence of a substantial informal sector. In addition, future studies may incorporate the rippling effect of minimum wages across industries that are not affected by minimum wages and how this might make certain states or countries less attractive for business and expansion locations. Grossman (1983) argues that an altered minimum wage would initiate a chain reaction determined by the elasticity of effort if individuals only make comparisons with the occupation levels they think to be directly below. This explains that workers at varying occupational levels compare their earnings to different reference groups but future research on the rippling effect across industries that are not affected by the minimum wage and all income groups is still sparse. Another way to advance the literature would be through identifying low wage earners and lower income brackets rather than incorporating food or retail industry workers as proxies. By accurately identifying lower income groups, the effect of an increase in minimum wage on employment would help determine a more accurate sense of how minimum wages influence the intentional targets of a minimum wage increase. Future studies could also study for the impact of an increase in minimum wages on preponing or delaying the retirement age depending on gender. In order to obtain and qualify for social security retirement benefits, one needs at least 40 credits that are equivalent to 10 years of work for the majority of Americans. To count towards your highest benefit levels, 35 years of your highest earnings are required. If the majority of women tend to earn lower wages, then in order to receive their highest levels of social security retirement benefits, women might delay their retirement age. To evaluate the impact of an increase in minimum wages on delaying or preponing the retirement age based on gender could explain a rationale behind the heterogeneous effects of minimum wages across industries.

8 Conclusion

Unlike previous literature, my study examines the effect of an increase in minimum wages on gender across all states of the U.S. by exploiting the natural experiment opportunity using the difference-in-differences estimation. The increase in minimum wages across states was implemented in 2015 and the states that increased their minimum wages were part of the *treatment* group and states that did not were part of the *control* group. This variation in wages caused by a rise in the minimum wages is exogenous to productivity and serves as a great opportunity to examine the effect of wages increases on gender. I obtain my dataset from IPUMS-CPS over the period 2013 to 2017 and I examine the effect of an increase in minimum wages on gender in the *Production* industry, the *Arts, Design, Entertainment, Sports and Media* industry and the *Transportation and Material Moving* industry in the U.S. Using the multivariate regressions to obtain difference-in-differences estimates, my results show that the largest impact of an increase in minimum wages in 2015 in the *Production* industry is on single women with one child and divorced women with one child. The $incwage_i$ of single women with one child increased by 9.60 percent and $incwage_i$ of divorced women with one child increased by 9.56 percent, significant at 1 percent level. My results for the *Arts, Design, Entertainment, Sports and Media* industry report that the implementation of an increase in minimum wages in 2015 had no impact on the $incwage_i$ of either men or women with different marital statuses or number of children. Although, the results were negative significant, the largest impact of an increase in minimum wages in 2015 is on single men with one child and divorced men with one child. The $incwage_i$ of single men with one child decreased by 9.86 percent and the $incwage_i$ of divorced men with one child decreased by 9.38 percent.

My results across all three industries conclude that women are not specifically affected by the implementation of an increase in minimum wages in the U.S in 2015. This could be because women with substantial work experienced are on average more qualified and hold higher occupation statuses when compared to men or women with fewer careers enhancing experiences. On the other hand, it could also be the case that women with different marital statuses with one or more number of children might be relying on government assistant programs and child care subsidies given that they work some minimum number of hours. Assuming that these women might fall under a subgroup of individuals that receive need and assistance programs from the federal government.

Based on my findings, future researchers can investigate the rippling effect of minimum wages across industries that are not affected by minimum wages and how this might make certain geographical locations much more beneficial for expansion. Future studies on the impact of an increase in minimum wages on delaying or preponing the retirement age based on gender could also be evaluated. Future research also needs to shed light on the most accurate methodology to model the effect of minimum wages as this could primarily influence a study's results. The prevalent literature on the methodologies for estimating the effectiveness of minimum wages as a tool of redistribution raise questions on whether a two-way fixed effects model or a difference-in-differences estimator is a better fit to examine impacts. However, the public policy of an increase in minimum wages is not a solution to universal poverty and depressed wages across the world. It does not boost a country's GDP or the rate of its capital productivity. Minimum wages are perceived as a tool of redistributing income to lower wage earners and are associated with wage inequality, though the magnitude of this effect is controversial. However, there may be uncertainty and risks of inefficient outcomes, and may not help those it is expected to help. More research is needed in the area of distinguishing lower wage earning groups before minimum wages can be more credibly rationalized as a tool for redistribution and poverty alleviation strategy.

Appendix

Table 1: Treatment and Control States

States	Treatment/Controls States
AK, AZ, AR, CO, CT, FL, HI, MD, MA, MO, MT, NE, NJ, NY, OH, OR, RI, SD, VT, WA, WV and D.C	Treatment States
AL, CA, DE, GA, ID, IL, IA, KS, KY, LA, ME, MI, MS, NH, NM, NC, ND, OK, PA, SC, TN, TX, UT, VA, WI, WY, AS, GU, MP, PR, VI, UM, FM, MH, PW	Control States

Table 2: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
logincwage	416,261	10.25	1.18	0	14.15
treatment	672,606	0.40	0.49	0	1
yeardummy	672,606	0.58	0.49	0	1
interaction	672,606	0.23	0.42	0	1

Table 3: Robust Results from the Production Industry

VARIABLES	(Single Men-No child) logincwage	(Single Men-1child) logincwage	(Single Women-No Child) logincwage	(Single Women-1 child) logincwage	(Divorced Men-No child) logincwage	(Divorced Men-1 Child) logincwage	(Divorced Women-No child) logincwage	(Divorced Women-1 child) logincwage	(Married Men-No child) logincwage	(Married Men-1 child) logincwage	(Married Women-No child) logincwage	(Married Women- 1 child) logincwage
treatment	-0.0595***	-0.0490***	-0.0598***	-0.0638***	-0.0594***	-0.0516***	-0.0598***	-0.0623***	-0.0595***	-0.0541***	-0.0605***	-0.0624***
	(0.0178)	(0.0179)	(0.0178)	(0.0179)	(0.0178)	(0.0178)	(0.0178)	(0.0179)	(0.0178)	(0.0178)	(0.0178)	(0.0178)
yeardummy	0.0417***	0.0432***	0.0421***	0.0389***	0.0418***	0.0429***	0.0422***	0.0383***	0.0419***	0.0429***	0.0420***	0.0432***
	(0.0133)	(0.0133)	(0.0134)	(0.0134)	(0.0133)	(0.0133)	(0.0134)	(0.0134)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
interaction	0.0921***	0.0809***	0.0919***	0.0960***	0.0918***	0.0836***	0.0920***	0.0956***	0.0921***	0.0880***	0.0926***	0.0929***
	(0.0251)	(0.0251)	(0.0251)	(0.0252)	(0.0251)	(0.0251)	(0.0251)	(0.0252)	(0.0251)	(0.0251)	(0.0250)	(0.0251)
Constant	10.26***	10.26***	10.25***	10.26***	10.26***	10.26***	10.25***	10.26***	10.26***	10.26***	10.26***	10.26***
	(0.00950)	(0.00950)	(0.00951)	(0.00953)	(0.00950)	(0.00949)	(0.00951)	(0.00954)	(0.00949)	(0.00950)	(0.00949)	(0.00949)
Observations	23,795	23,675	23,740	23,582	23,800	23,696	23,744	23,597	23,814	23,743	23,827	23,775
R-squared	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Robust Results from the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	(Single Men-No child) logincwage	(Single Men-1child) logincwage	(Single Women-No Child) logincwage	(Single Women-1 child) logincwage	(Divorced Men-No child) logincwage	(Divorced Men-1 Child) logincwage	(Divorced Women-No child) logincwage	(Divorced Women-1 child) logincwage	(Married Men-No child) logincwage	(Married Men-1 child) logincwage	(Married Women-No child) logincwage	(Married Women- 1 child) logincwage
treatment	0.0146	0.0197	0.0117	0.0172	0.0146	0.0193	0.0117	0.0220	0.0153	0.0147	0.0148	0.00131
	(0.0496)	(0.0495)	(0.0497)	(0.0498)	(0.0497)	(0.0495)	(0.0497)	(0.0497)	(0.0496)	(0.0498)	(0.0496)	(0.0495)
yeardummy	0.194***	0.191***	0.183***	0.187***	0.191***	0.187***	0.184***	0.188***	0.195***	0.193***	0.188***	0.186***
	(0.0417)	(0.0416)	(0.0418)	(0.0419)	(0.0417)	(0.0416)	(0.0418)	(0.0418)	(0.0417)	(0.0419)	(0.0417)	(0.0416)
interaction	-0.0844	-0.0986	-0.0732	-0.0796	-0.0813	-0.0938	-0.0746	-0.0817	-0.0857	-0.0825	-0.0781	-0.0647
	(0.0697)	(0.0696)	(0.0699)	(0.0699)	(0.0697)	(0.0696)	(0.0699)	(0.0698)	(0.0696)	(0.0700)	(0.0697)	(0.0695)
Constant	10.18***	10.20***	10.18***	10.18***	10.18***	10.20***	10.18***	10.18***	10.18***	10.18***	10.18***	10.19***
	(0.0300)	(0.0300)	(0.0301)	(0.0302)	(0.0301)	(0.0300)	(0.0301)	(0.0301)	(0.0300)	(0.0301)	(0.0301)	(0.0300)
Observations	6,280	6,221	6,265	6,215	6,282	6,224	6,267	6,216	6,287	6,255	6,290	6,266
R-squared	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Robust Results from the Transportation and Material Moving Industry

VARIABLES	(Single Men-No child) logincwage	(Single Men-1child) logincwage	(Single Women-No Child) logincwage	(Single Women-1 child) logincwage	(Divorced Men-No child) logincwage	(Divorced Men-1 Child) logincwage	(Divorced Women-No child) logincwage	(Divorced Women-1 child) logincwage	(Married Men-No child) logincwage	(Married Men-1 child) logincwage	(Married Women-No child) logincwage	(Married Women- 1 child) logincwage
treatment	-0.0874***	-0.0880***	-0.0823***	-0.0790***	-0.0872***	-0.0909***	-0.0826***	-0.0752***	-0.0870***	-0.0899***	-0.0873***	-0.0859***
	(0.0195)	(0.0195)	(0.0195)	(0.0197)	(0.0195)	(0.0194)	(0.0195)	(0.0197)	(0.0195)	(0.0195)	(0.0195)	(0.0195)
yeardummy	0.0765***	0.0782***	0.0791***	0.0731***	0.0765***	0.0791***	0.0788***	0.0772***	0.0767***	0.0770***	0.0780***	0.0773***
	(0.0154)	(0.0155)	(0.0155)	(0.0156)	(0.0154)	(0.0154)	(0.0155)	(0.0156)	(0.0154)	(0.0154)	(0.0155)	(0.0155)
interaction	0.0621**	0.0654**	0.0577**	0.0556**	0.0620**	0.0680**	0.0575**	0.0484*	0.0616**	0.0669**	0.0624**	0.0610**
	(0.0270)	(0.0270)	(0.0271)	(0.0274)	(0.0270)	(0.0270)	(0.0271)	(0.0274)	(0.0270)	(0.0270)	(0.0270)	(0.0271)
Constant	10.07***	10.07***	10.07***	10.08***	10.07***	10.07***	10.07***	10.08***	10.07***	10.07***	10.07***	10.07***
	(0.0110)	(0.0110)	(0.0110)	(0.0111)	(0.0110)	(0.0110)	(0.0110)	(0.0111)	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Observations	24,293	24,219	24,145	23,592	24,293	24,229	24,158	23,636	24,300	24,247	24,272	24,131
R-squared	0.003	0.003	0.003	0.003	0.003	0.004	0.003	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Production Industry – Results without correcting for Heteroscedasticity

Table 6 : Heterogeneous effects on Single Men in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0500***	-0.0500***	-0.0452**	-0.0448**	-0.0448**
	(0.0183)	(0.0183)	(0.0184)	(0.0184)	(0.0184)
yeardummy	0.0658***	0.0658***	0.0657***	0.0659***	0.0658***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)	(0.0138)
interaction	0.0631***	0.0631***	0.0595**	0.0593**	0.0595**
	(0.0240)	(0.0240)	(0.0240)	(0.0240)	(0.0240)
Constant	10.25***	10.25***	10.25***	10.25***	10.25***
	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)
Observations	23,792	23,792	23,639	23,631	23,627
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Heterogeneous effects on Single Women in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0514***	-0.0512***	-0.0512***	-0.0514***	-0.0513***
	(0.0183)	(0.0184)	(0.0184)	(0.0184)	(0.0184)
yeardummy	0.0656***	0.0641***	0.0640***	0.0639***	0.0640***
	(0.0138)	(0.0138)	(0.0139)	(0.0139)	(0.0139)
interaction	0.0643***	0.0642***	0.0642***	0.0643***	0.0644***
	(0.0240)	(0.0241)	(0.0241)	(0.0241)	(0.0241)
Constant	10.25***	10.25***	10.25***	10.25***	10.25***
	(0.0105)	(0.0106)	(0.0106)	(0.0106)	(0.0106)
Observations	23,738	23,568	23,528	23,503	23,503
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Heterogeneous effects on Divorced Men in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0500***	-0.0464**	-0.0452**	-0.0448**	-0.0448**
	(0.0183)	(0.0184)	(0.0184)	(0.0184)	(0.0184)
yeardummy	0.0658***	0.0661***	0.0657***	0.0659***	0.0658***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)	(0.0138)
interaction	0.0631***	0.0608**	0.0595**	0.0593**	0.0595**
	(0.0240)	(0.0240)	(0.0240)	(0.0240)	(0.0240)
Constant	10.25***	10.25***	10.25***	10.25***	10.25***
	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)
Observations	23,792	23,662	23,639	23,631	23,627
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Heterogeneous effects on Divorced Women in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0514***	-0.0512***	-0.0512***	-0.0514***	-0.0513***
	(0.0183)	(0.0184)	(0.0184)	(0.0184)	(0.0184)
yeardummy	0.0656***	0.0641***	0.0640***	0.0639***	0.0640***
	(0.0138)	(0.0138)	(0.0139)	(0.0139)	(0.0139)
interaction	0.0643***	0.0642***	0.0642***	0.0643***	0.0644***
	(0.0240)	(0.0241)	(0.0241)	(0.0241)	(0.0241)
Constant	10.25***	10.25***	10.25***	10.25***	10.25***
	(0.0105)	(0.0106)	(0.0106)	(0.0106)	(0.0106)
Observations	23,738	23,568	23,528	23,503	23,503
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Heterogeneous effects on Married Men in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0518***	-0.0518***	-0.0518***	-0.0518***	-0.0518***
	(0.0183)	(0.0183)	(0.0183)	(0.0183)	(0.0183)
yeardummy	0.0660***	0.0665***	0.0664***	0.0664***	0.0664***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)	(0.0138)
interaction	0.0645***	0.0647***	0.0648***	0.0647***	0.0648***
	(0.0239)	(0.0239)	(0.0239)	(0.0239)	(0.0239)
Constant	10.25***	10.25***	10.25***	10.25***	10.25***
	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)
Observations	23,841	23,830	23,827	23,828	23,827
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Heterogeneous effects on Married Women in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0517***	-0.0518***	-0.0517***	-0.0517***	-0.0517***
	(0.0183)	(0.0183)	(0.0183)	(0.0183)	(0.0183)
yeardummy	0.0661***	0.0662***	0.0662***	0.0662***	0.0662***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)	(0.0138)
interaction	0.0644***	0.0645***	0.0645***	0.0645***	0.0645***
	(0.0239)	(0.0239)	(0.0239)	(0.0239)	(0.0239)
Constant	10.25***	10.25***	10.25***	10.25***	10.25***
	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)
Observations	23,841	23,829	23,825	23,825	23,825
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Arts, Design, Entertainment, Sports and Media Industry - Results without correcting for Heteroscedasticity

Table 12: Heterogeneous effects on Single Men in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.142***	0.149***	0.149***	0.149***	0.149***
	(0.0524)	(0.0525)	(0.0525)	(0.0525)	(0.0525)
yeardummy	0.171***	0.170***	0.174***	0.176***	0.175***
	(0.0450)	(0.0451)	(0.0451)	(0.0451)	(0.0451)
interaction	-0.155**	-0.164**	-0.168**	-0.169**	-0.168**
	(0.0686)	(0.0688)	(0.0688)	(0.0688)	(0.0688)
Constant	10.18***	10.19***	10.19***	10.19***	10.19***
	(0.0345)	(0.0346)	(0.0346)	(0.0346)	(0.0346)
Observations	6,280	6,210	6,206	6,204	6,202
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13 : Heterogeneous effects on Single Women in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.137***	0.135**	0.135**	0.134**	0.134**
	(0.0525)	(0.0527)	(0.0527)	(0.0527)	(0.0527)
yeardummy	0.161***	0.169***	0.167***	0.166***	0.165***
	(0.0451)	(0.0451)	(0.0452)	(0.0452)	(0.0452)
interaction	-0.143**	-0.149**	-0.148**	-0.145**	-0.145**
	(0.0688)	(0.0689)	(0.0690)	(0.0690)	(0.0690)
Constant	10.19***	10.18***	10.18***	10.18***	10.18***
	(0.0346)	(0.0346)	(0.0346)	(0.0346)	(0.0346)
Observations	6,265	6,206	6,192	6,186	6,185
R-squared	0.002	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14 : Heterogeneous effects on Divorced Men in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.142***	0.149***	0.149***	0.149***	0.149***
	(0.0524)	(0.0525)	(0.0525)	(0.0525)	(0.0525)
yeardummy	0.171***	0.170***	0.174***	0.176***	0.175***
	(0.0450)	(0.0451)	(0.0451)	(0.0451)	(0.0451)
interaction	-0.155**	-0.164**	-0.168**	-0.169**	-0.168**
	(0.0686)	(0.0688)	(0.0688)	(0.0688)	(0.0688)
Constant	10.18***	10.19***	10.19***	10.19***	10.19***
	(0.0345)	(0.0346)	(0.0346)	(0.0346)	(0.0346)
Observations	6,280	6,210	6,206	6,204	6,202
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Heterogeneous effects on Divorced Women in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.137***	0.135**	0.135**	0.134**	0.134**
	(0.0525)	(0.0527)	(0.0527)	(0.0527)	(0.0527)
yeardummy	0.161***	0.169***	0.167***	0.166***	0.165***
	(0.0451)	(0.0451)	(0.0452)	(0.0452)	(0.0452)
interaction	-0.143**	-0.149**	-0.148**	-0.145**	-0.145**
	(0.0688)	(0.0689)	(0.0690)	(0.0690)	(0.0690)
Constant	10.19***	10.18***	10.18***	10.18***	10.18***
	(0.0346)	(0.0346)	(0.0346)	(0.0346)	(0.0346)
Observations	6,265	6,206	6,192	6,186	6,185
R-squared	0.002	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Heterogeneous effects on Married Men in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.140***	0.141***	0.141***	0.141***	0.141***
	(0.0524)	(0.0525)	(0.0525)	(0.0525)	(0.0525)
yeardummy	0.167***	0.166***	0.166***	0.166***	0.166***
	(0.0450)	(0.0450)	(0.0450)	(0.0450)	(0.0450)
interaction	-0.151**	-0.148**	-0.148**	-0.148**	-0.148**
	(0.0686)	(0.0687)	(0.0687)	(0.0687)	(0.0687)
Constant	10.18***	10.18***	10.18***	10.18***	10.18***
	(0.0345)	(0.0346)	(0.0346)	(0.0346)	(0.0346)
Observations	6,294	6,283	6,283	6,283	6,283
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Heterogeneous effects on Married Women in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.140***	0.135***	0.135***	0.135***	0.135***
	(0.0524)	(0.0524)	(0.0524)	(0.0524)	(0.0524)
yeardummy	0.167***	0.169***	0.169***	0.169***	0.169***
	(0.0450)	(0.0449)	(0.0449)	(0.0449)	(0.0449)
interaction	-0.151**	-0.148**	-0.148**	-0.148**	-0.148**
	(0.0686)	(0.0686)	(0.0686)	(0.0686)	(0.0686)
Constant	10.18***	10.18***	10.18***	10.18***	10.18***
	(0.0345)	(0.0345)	(0.0345)	(0.0345)	(0.0345)
Observations	6,293	6,284	6,285	6,284	6,284
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Transportation and Material Moving Industry - Results without correcting for Heteroscedasticity

Table 18: Hetergogenous effects on Single Men in the Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0331	-0.0332	-0.0332	-0.0334	-0.0334
	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0207)
yeardummy	0.104***	0.106***	0.106***	0.106***	0.106***
	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0164)
interaction	0.00594	0.00741	0.00723	0.00705	0.00739
	(0.0269)	(0.0269)	(0.0269)	(0.0269)	(0.0269)
Constant	10.07***	10.07***	10.08***	10.08***	10.08***
	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0125)
Observations	24,293	24,219	24,202	24,202	24,201
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Hetergogenous effects on Single Women in the Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0294	-0.0278	-0.0280	-0.0265	-0.0272
	(0.0208)	(0.0209)	(0.0210)	(0.0210)	(0.0210)
yeardummy	0.107***	0.104***	0.105***	0.106***	0.106***
	(0.0165)	(0.0166)	(0.0166)	(0.0166)	(0.0166)
interaction	0.00244	0.00124	0.00163	0.000167	0.000934
	(0.0270)	(0.0273)	(0.0273)	(0.0274)	(0.0274)
Constant	10.07***	10.08***	10.08***	10.08***	10.08***
	(0.0125)	(0.0126)	(0.0126)	(0.0127)	(0.0127)
Observations	24,145	23,592	23,516	23,476	23,474
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Hetergogenous effects on Divorced Men in the Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0328	-0.0343*	-0.0341*	-0.0342*	-0.0342*
	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0207)
yeardummy	0.104***	0.107***	0.106***	0.106***	0.106***
	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0164)
interaction	0.00578	0.00840	0.00807	0.00789	0.00823
	(0.0269)	(0.0269)	(0.0269)	(0.0269)	(0.0269)
Constant	10.07***	10.07***	10.08***	10.08***	10.08***
	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0125)
Observations	24,293	24,229	24,212	24,212	24,211
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: Hetergogenous effects on Divorced Women in the Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0298	-0.0267	-0.0273	-0.0258	-0.0265
	(0.0208)	(0.0209)	(0.0210)	(0.0210)	(0.0210)
yeardummy	0.107***	0.107***	0.108***	0.108***	0.108***
	(0.0165)	(0.0166)	(0.0166)	(0.0166)	(0.0166)
interaction	0.00221	-0.00280	-0.00278	-0.00420	-0.00344
	(0.0270)	(0.0273)	(0.0273)	(0.0274)	(0.0274)
Constant	10.07***	10.08***	10.08***	10.08***	10.08***
	(0.0125)	(0.0126)	(0.0127)	(0.0127)	(0.0127)
Observations	24,158	23,636	23,566	23,529	23,527
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22: Heterogeneous effects on Married Men in the Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0325	-0.0334	-0.0331	-0.0331	-0.0331
	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0207)
yeardummy	0.104***	0.105***	0.105***	0.105***	0.105***
	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0164)
interaction	0.00518	0.00785	0.00753	0.00755	0.00755
	(0.0269)	(0.0269)	(0.0269)	(0.0269)	(0.0269)
Constant	10.07***	10.07***	10.07***	10.07***	10.07***
	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0125)
Observations	24,300	24,247	24,232	24,231	24,231
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 23: Heterogeneous effects on Married Women in the Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0326	-0.0319	-0.0317	-0.0317	-0.0317
	(0.0207)	(0.0207)	(0.0208)	(0.0208)	(0.0208)
yeardummy	0.105***	0.105***	0.106***	0.105***	0.105***
	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0164)
interaction	0.00593	0.00461	0.00492	0.00502	0.00502
	(0.0269)	(0.0270)	(0.0270)	(0.0270)	(0.0270)
Constant	10.07***	10.08***	10.07***	10.07***	10.07***
	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0125)
Observations	24,272	24,131	24,099	24,093	24,093
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Checks – Heteroskedasticity

Robust Results for the Production Industry

Table 24: Robust heterogeneous effects on Single Men in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0595***	-0.0490***	-0.0489***	-0.0485***	-0.0485***
	(0.0178)	(0.0179)	(0.0179)	(0.0179)	(0.0179)
yeardummy	0.0417***	0.0432***	0.0426***	0.0426***	0.0427***
	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
interaction	0.0921***	0.0809***	0.0812***	0.0808***	0.0808***
	(0.0251)	(0.0251)	(0.0251)	(0.0251)	(0.0251)
Constant	10.26***	10.26***	10.26***	10.26***	10.26***
	(0.00950)	(0.00950)	(0.00950)	(0.00950)	(0.00950)
Observations	23,795	23,675	23,654	23,645	23,642

R-squared	0.002	0.002	0.002	0.002	0.002

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Robust heterogeneous effects on Single Women in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0598***	-0.0638***	-0.0636***	-0.0637***	-0.0636***
	(0.0178)	(0.0179)	(0.0179)	(0.0179)	(0.0179)
yeardummy	0.0421***	0.0389***	0.0391***	0.0392***	0.0392***
	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0134)
interaction	0.0919***	0.0960***	0.0963***	0.0960***	0.0960***
	(0.0251)	(0.0252)	(0.0252)	(0.0252)	(0.0252)
Constant	10.25***	10.26***	10.26***	10.26***	10.26***
	(0.00951)	(0.00953)	(0.00954)	(0.00954)	(0.00954)
Observations	23,740	23,582	23,544	23,519	23,519
R-squared	0.002	0.002	0.002	0.002	0.002

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26: Robust heterogeneous effects on Divorced Men in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0594***	-0.0516***	-0.0515***	-0.0511***	-0.0511***
	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0178)
yeardummy	0.0418***	0.0429***	0.0424***	0.0425***	0.0425***
	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
interaction	0.0918***	0.0836***	0.0837***	0.0832***	0.0832***
	(0.0251)	(0.0251)	(0.0251)	(0.0251)	(0.0251)
Constant	10.26***	10.26***	10.26***	10.26***	10.26***
	(0.00950)	(0.00949)	(0.00950)	(0.00949)	(0.00950)
Observations	23,800	23,696	23,679	23,672	23,668
R-squared	0.002	0.002	0.002	0.002	0.002

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 27: Robust heterogeneous effects on Divorced Women in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0598***	-0.0623***	-0.0628***	-0.0626***	-0.0625***
	(0.0178)	(0.0179)	(0.0179)	(0.0179)	(0.0179)
yeardummy	0.0422***	0.0383***	0.0379***	0.0384***	0.0384***
	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0134)
interaction	0.0920***	0.0956***	0.0966***	0.0960***	0.0961***
	(0.0251)	(0.0252)	(0.0252)	(0.0252)	(0.0252)
Constant	10.25***	10.26***	10.26***	10.26***	10.26***
	(0.00951)	(0.00954)	(0.00954)	(0.00955)	(0.00955)
Observations	23,744	23,597	23,561	23,537	23,537
R-squared	0.002	0.002	0.002	0.002	0.002

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 28: Robust heterogeneous effects on Married Men in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0595***	-0.0541***	-0.0540***	-0.0536***	-0.0536***
	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0178)
yeardummy	0.0419***	0.0429***	0.0425***	0.0426***	0.0426***
	(0.0133)	(0.0133)	(0.0133)	(0.0134)	(0.0134)
interaction	0.0921***	0.0880***	0.0882***	0.0877***	0.0878***
	(0.0251)	(0.0251)	(0.0251)	(0.0251)	(0.0251)
Constant	10.26***	10.26***	10.26***	10.26***	10.26***
	(0.00949)	(0.00950)	(0.00951)	(0.00951)	(0.00951)
Observations	23,814	23,743	23,733	23,725	23,724
R-squared	0.002	0.002	0.002	0.002	0.002

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 29: Robust heterogeneous effects on Married Women in the Production Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0605***	-0.0624***	-0.0617***	-0.0620***	-0.0620***
	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0178)
yeardummy	0.0420***	0.0432***	0.0440***	0.0436***	0.0436***
	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
interaction	0.0926***	0.0929***	0.0920***	0.0924***	0.0924***
	(0.0250)	(0.0251)	(0.0251)	(0.0251)	(0.0251)
Constant	10.26***	10.26***	10.26***	10.26***	10.26***
	(0.00949)	(0.00949)	(0.00950)	(0.00950)	(0.00950)
Observations	23,827	23,775	23,761	23,759	23,759
R-squared	0.002	0.002	0.002	0.002	0.002

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robust Results for the Arts, Design, Entertainment, Sports and Media Industry

Table 30: Robust heterogeneous effects on Single Men in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.0146	0.0197	0.0207	0.0201	0.0201
	(0.0496)	(0.0495)	(0.0495)	(0.0495)	(0.0495)
yeardummy	0.194***	0.191***	0.198***	0.198***	0.198***
	(0.0417)	(0.0416)	(0.0416)	(0.0416)	(0.0416)
interaction	-0.0844	-0.0986	-0.106	-0.106	-0.105
	(0.0697)	(0.0696)	(0.0695)	(0.0696)	(0.0696)
Constant	10.18***	10.20***	10.20***	10.20***	10.20***
	(0.0300)	(0.0300)	(0.0300)	(0.0300)	(0.0300)
Observations	6,280	6,221	6,217	6,215	6,213
R-squared	0.004	0.004	0.004	0.004	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 31: Robust heterogeneous effects on Single Women in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.0117	0.0172	0.0148	0.0145	0.0145
	(0.0497)	(0.0498)	(0.0498)	(0.0498)	(0.0498)
yeardummy	0.183***	0.187***	0.184***	0.183***	0.183***
	(0.0418)	(0.0419)	(0.0419)	(0.0419)	(0.0419)
interaction	-0.0732	-0.0796	-0.0795	-0.0772	-0.0766
	(0.0699)	(0.0699)	(0.0700)	(0.0700)	(0.0700)
Constant	10.18***	10.18***	10.18***	10.18***	10.18***
	(0.0301)	(0.0302)	(0.0302)	(0.0302)	(0.0302)
Observations	6,265	6,215	6,201	6,195	6,194
R-squared	0.004	0.004	0.004	0.004	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 32: Robust heterogeneous effects on Divorced Men in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.0146	0.0193	0.0204	0.0197	0.0197
	(0.0497)	(0.0495)	(0.0495)	(0.0495)	(0.0495)
yeardummy	0.191***	0.187***	0.191***	0.191***	0.191***
	(0.0417)	(0.0416)	(0.0416)	(0.0416)	(0.0417)
interaction	-0.0813	-0.0938	-0.0982	-0.0983	-0.0974
	(0.0697)	(0.0696)	(0.0696)	(0.0696)	(0.0696)
Constant	10.18***	10.20***	10.20***	10.20***	10.20***
	(0.0301)	(0.0300)	(0.0300)	(0.0300)	(0.0300)
Observations	6,282	6,224	6,222	6,220	6,218
R-squared	0.004	0.004	0.004	0.004	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 33: Robust heterogeneous effects on Divorced Women in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.0117	0.0220	0.0196	0.0192	0.0192
	(0.0497)	(0.0497)	(0.0498)	(0.0498)	(0.0498)
yeardummy	0.184***	0.188***	0.187***	0.186***	0.185***
	(0.0418)	(0.0418)	(0.0418)	(0.0419)	(0.0419)
interaction	-0.0746	-0.0817	-0.0830	-0.0807	-0.0801
	(0.0699)	(0.0698)	(0.0699)	(0.0700)	(0.0700)
Constant	10.18***	10.18***	10.18***	10.18***	10.18***
	(0.0301)	(0.0301)	(0.0301)	(0.0302)	(0.0302)
Observations	6,267	6,216	6,204	6,198	6,197
R-squared	0.004	0.004	0.004	0.004	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 34: Robust heterogeneous effects on Married Men in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.0153	0.0147	0.0152	0.0152	0.0152
	(0.0496)	(0.0498)	(0.0497)	(0.0497)	(0.0497)
yeardummy	0.195***	0.193***	0.199***	0.199***	0.199***
	(0.0417)	(0.0419)	(0.0418)	(0.0418)	(0.0418)
interaction	-0.0857	-0.0825	-0.0891	-0.0889	-0.0889
	(0.0696)	(0.0700)	(0.0699)	(0.0699)	(0.0699)
Constant	10.18***	10.18***	10.18***	10.18***	10.18***
	(0.0300)	(0.0301)	(0.0301)	(0.0301)	(0.0301)
Observations	6,287	6,255	6,250	6,249	6,249
R-squared	0.004	0.004	0.004	0.004	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 35: Robust heterogeneous effects on Married Women in the Arts, Design, Entertainment, Sports and Media Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	0.0148	0.00131	0.00131	0.00131	0.00131
	(0.0496)	(0.0495)	(0.0495)	(0.0495)	(0.0495)
yeardummy	0.188***	0.186***	0.185***	0.184***	0.184***
	(0.0417)	(0.0416)	(0.0416)	(0.0416)	(0.0416)
interaction	-0.0781	-0.0647	-0.0635	-0.0633	-0.0633
	(0.0697)	(0.0695)	(0.0695)	(0.0695)	(0.0695)
Constant	10.18***	10.19***	10.19***	10.19***	10.19***
	(0.0301)	(0.0300)	(0.0300)	(0.0300)	(0.0300)
Observations	6,290	6,266	6,264	6,263	6,263
R-squared	0.004	0.004	0.004	0.004	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robust Results for the Transportation and Material Moving Industry

Table 36: Robust heterogeneous effects on Single Men in Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0874***	-0.0880***	-0.0875***	-0.0877***	-0.0877***
	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)
yeardummy	0.0765***	0.0782***	0.0781***	0.0779***	0.0779***
	(0.0154)	(0.0155)	(0.0155)	(0.0155)	(0.0155)
interaction	0.0621**	0.0654**	0.0651**	0.0652**	0.0653**
	(0.0270)	(0.0270)	(0.0271)	(0.0271)	(0.0271)
Constant	10.07***	10.07***	10.07***	10.07***	10.07***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Observations	24,293	24,219	24,202	24,202	24,201
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 37: Robust heterogeneous effects on Single Women in Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0823***	-0.0790***	-0.0820***	-0.0781***	-0.0789***
	(0.0195)	(0.0197)	(0.0198)	(0.0198)	(0.0198)
yeardummy	0.0791***	0.0731***	0.0753***	0.0754***	0.0753***
	(0.0155)	(0.0156)	(0.0156)	(0.0157)	(0.0157)
interaction	0.0577**	0.0556**	0.0590**	0.0554**	0.0562**
	(0.0271)	(0.0274)	(0.0274)	(0.0275)	(0.0275)
Constant	10.07***	10.08***	10.08***	10.08***	10.08***
	(0.0110)	(0.0111)	(0.0111)	(0.0111)	(0.0111)
Observations	24,145	23,592	23,516	23,476	23,474
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 38: Robust heterogeneous effects on Divorced Men in Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0872***	-0.0909***	-0.0903***	-0.0904***	-0.0904***
	(0.0195)	(0.0194)	(0.0195)	(0.0195)	(0.0195)
yeardummy	0.0765***	0.0791***	0.0789***	0.0788***	0.0788***
	(0.0154)	(0.0154)	(0.0154)	(0.0154)	(0.0154)
interaction	0.0620**	0.0680**	0.0675**	0.0676**	0.0677**
	(0.0270)	(0.0270)	(0.0270)	(0.0270)	(0.0270)
Constant	10.07***	10.07***	10.07***	10.07***	10.07***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Observations	24,293	24,229	24,212	24,212	24,211
R-squared	0.003	0.004	0.004	0.004	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 39: Robust heterogeneous effects on Divorced Women in Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0826***	-0.0752***	-0.0784***	-0.0745***	-0.0754***
	(0.0195)	(0.0197)	(0.0198)	(0.0198)	(0.0198)
yeardummy	0.0788***	0.0772***	0.0787***	0.0790***	0.0789***
	(0.0155)	(0.0156)	(0.0156)	(0.0157)	(0.0157)
interaction	0.0575**	0.0484*	0.0514*	0.0478*	0.0487*
	(0.0271)	(0.0274)	(0.0274)	(0.0275)	(0.0275)
Constant	10.07***	10.08***	10.08***	10.08***	10.08***
	(0.0110)	(0.0111)	(0.0111)	(0.0111)	(0.0111)
Observations	24,158	23,636	23,566	23,529	23,527
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 40: Robust heterogeneous effects on Married Men in Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0870***	-0.0899***	-0.0893***	-0.0893***	-0.0893***
	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)
yeardummy	0.0767***	0.0770***	0.0768***	0.0768***	0.0768***
	(0.0154)	(0.0154)	(0.0154)	(0.0154)	(0.0154)
interaction	0.0616**	0.0669**	0.0664**	0.0665**	0.0665**
	(0.0270)	(0.0270)	(0.0270)	(0.0270)	(0.0270)
Constant	10.07***	10.07***	10.07***	10.07***	10.07***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Observations	24,300	24,247	24,232	24,231	24,231
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 41: Robust heterogeneous effects on Divorced Women in Transportation and Material Moving Industry

VARIABLES	logincwage (No child) (1)	logincwage (1 child) (2)	logincwage (2 children) (3)	logincwage (3 children) (4)	logincwage (4 children) (5)
treatment	-0.0873***	-0.0859***	-0.0855***	-0.0855***	-0.0855***
	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)
yeardummy	0.0780***	0.0773***	0.0788***	0.0785***	0.0785***
	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0155)
interaction	0.0624**	0.0610**	0.0611**	0.0612**	0.0612**
	(0.0270)	(0.0271)	(0.0271)	(0.0271)	(0.0271)
Constant	10.07***	10.07***	10.07***	10.07***	10.07***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Observations	24,272	24,131	24,099	24,093	24,093
R-squared	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Checks – VIFS

Production Industry

Table 42: VIFS for Single Men

VARIABLES	Single Men (No Child) VIF	Single Men (1 Child) VIF	Single Men (2 Children) VIF	Single Men (3 Children) VIF	Single Men (4 Children) VIF
interaction	2.91	2.91	2.91	2.91	2.91
treatment	2.41	2.41	2.41	2.41	2.41
yeardummy	1.50	1.49	1.49	1.49	1.49
Mean VIF	2.27	2.27	2.27	2.27	2.27

Table 43: VIFS for Single Women

VARIABLES	Single Women (No Child) VIF	Single Women (1 Child) VIF	Single Women (2 Children) VIF	Single Women (3 Children) VIF	Single Women (4 Children) VIF
interaction	2.91	2.91	2.91	2.91	2.91
treatment	2.40	2.40	2.41	2.40	2.40
yeardummy	1.50	1.50	1.49	1.49	1.49
Mean VIF	2.27	2.27	2.27	2.27	2.27

Table 44: VIFS for Divorced Men

VARIABLES	Divorced Men (No Child) VIF	Divorced Men (1 Child) VIF	Divorced Men (2 Children) VIF	Divorced Men (3 Children) VIF	Divorced Men (4 Children) VIF
interaction	2.91	2.91	2.91	2.91	2.91
treatment	2.41	2.41	2.41	2.41	2.41
yeardummy	1.50	1.49	1.49	1.49	1.49
Mean VIF	2.27	2.27	2.27	2.27	2.27

Table 45: VIFS for Divorced Women

VARIABLES	Divorced Women (No Child) VIF	Divorced Women (1 Child) VIF	Divorced Women (2 Children) VIF	Divorced Women (3 Children) VIF	Divorced Women (4 Children) VIF
interaction	2.91	2.91	2.91	2.91	2.91
treatment	2.40	2.40	2.40	2.40	2.40
yeardummy	1.50	1.49	1.49	1.49	1.49
Mean VIF	2.27	2.27	2.27	2.27	2.27

Table 46: VIFS for Married Men

VARIABLES	Married Men (No Child) VIF	Married Men (1 Child) VIF	Married Men (2 Children) VIF	Married Men (3 Children) VIF	Married Men (4 Children) VIF
interaction	2.91	2.91	2.91	2.91	2.91
treatment	2.41	2.41	2.41	2.41	2.41
yeardummy	1.50	1.49	1.49	1.49	1.49
Mean VIF	2.27	2.27	2.27	2.27	2.27

Table 47: VIFS for Married Women

VARIABLES	Married Women (No Child) VIF	Married Women (1 Child) VIF	Married Women (2 Children) VIF	Married Women (3 Children) VIF	Married Women (4 Children) VIF
interaction	2.91	2.91	2.91	2.91	2.91
treatment	2.41	2.40	2.41	2.41	2.41
yeardummy interaction	1.50	1.50	1.50	1.50	1.50
Mean VIF	2.27	2.27	2.27	2.27	2.27

Arts, Design, Entertainment, Sports and Media Industry

Table 48: VIFS for Single Men

VARIABLES	Single Men (No Child) VIF	Single Men (1 Child) VIF	Single Men (2 Children) VIF	Single Men (3 Children) VIF	Single Men (4 Children) VIF
interaction	3.14	3.13	3.14	3.13	3.13
treatment	2.40	2.40	2.40	2.40	2.40
yeardummy	1.75	1.75	1.75	1.75	1.75
Mean VIF	2.43	2.43	2.43	2.43	2.43

Table 49: VIFS for Single Women

VARIABLES	Single Women (No Child) VIF	Single Women (1 Child) VIF	Single Women (2 Children) VIF	Single Women (3 Children) VIF	Single Women (4 Children) VIF
interaction	3.14	3.14	3.14	3.14	3.14
treatment	2.40	2.40	2.40	2.40	2.40
yeardummy	1.75	1.75	1.75	1.75	1.75
Mean VIF	2.43	2.43	2.43	2.43	2.43

Table 50: VIFS for Divorced Men

VARIABLES	Divorced Men (No Child) VIF	Divorced Men (1 Child) VIF	Divorced Men (2 Children) VIF	Divorced Men (3 Children) VIF	Divorced Men (4 Children) VIF
interaction	3.14	3.14	3.14	3.14	3.14
treatment	2.40	2.40	2.40	2.40	2.40
yeardummy	1.75	1.75	1.75	1.75	1.75
Mean VIF	2.43	2.43	2.43	2.43	2.43

Table 51: VIFS for Divorced Women

VARIABLES	Divorced Women (No Child) VIF	Divorced Women (1 Child) VIF	Divorced Women (2 Children) VIF	Divorced Women (3 Children) VIF	Divorced Women (4 Children) VIF
interaction	3.14	3.14	3.14	3.14	3.14
treatment	2.40	2.40	2.40	2.40	2.40
yeardummy	1.75	1.75	1.75	1.75	1.75
Mean VIF	2.43	2.43	2.43	2.43	2.43

Table 52: VIFS for Married Men

VARIABLES	Married Men (No Child) VIF	Married Men (1 Child) VIF	Married Men (2 Children) VIF	Married Men (3 Children) VIF	Married Men (4 Children) VIF
interaction	3.14	3.14	3.13	3.13	3.13
treatment	2.40	2.40	2.40	2.40	2.40
yeardummy	1.75	1.75	1.75	1.75	1.75
Mean VIF	2.43	2.43	2.43	2.43	2.43

Table 53: VIFS for Married Women

VARIABLES	Married Women (No Child) VIF	Married Women (1 Child) VIF	Married Women (2 Children) VIF	Married Women (3 Children) VIF	Married Women (4 Children) VIF
interaction	3.14	3.14	3.14	3.14	3.14
treatment	2.40	2.40	2.40	2.40	2.40
yeardummy	1.75	1.75	1.75	1.75	1.75
Mean VIF	2.43	2.43	2.43	2.43	2.43

Transportation and Material Moving Industry

Table 54: VIFS for Single Men

VARIABLES	Single Men (No Child) VIF	Single Men (1 Child) VIF	Single Men (2 Children) VIF	Single Men (3 Children) VIF	Single Men (4 Children) VIF
interaction	3.06	3.05	3.05	3.05	3.05
treatment	2.44	2.44	2.44	2.44	2.44
yeardummy	1.59	1.59	1.59	1.59	1.59
Mean VIF	2.36	2.36	2.36	2.36	2.36

Table 55: VIFS for Single Women

VARIABLES	Single Women (No Child) VIF	Single Women (1 Child) VIF	Single Women (2 Children) VIF	Single Women (3 Children) VIF	Single Women (4 Children) VIF
interaction	3.06	3.05	3.05	3.05	3.05
treatment	2.44	2.44	2.44	2.44	2.44
yeardummy	1.59	1.59	1.59	1.59	1.59
Mean VIF	2.36	2.36	2.36	2.36	2.36

Table 56: VIFS for Divorced Men

VARIABLES	Divorced Men (No Child) VIF	Divorced Men (1 Child) VIF	Divorced Men (2 Children) VIF	Divorced Men (3 Children) VIF	Divorced Men (4 Children) VIF
interaction	3.06	3.06	3.05	3.06	3.05
treatment	2.44	2.44	2.44	2.44	2.44
yeardummy	1.59	1.59	1.59	1.59	1.59
Mean VIF	2.36	2.36	2.36	2.36	2.36

Table 57: VIFS for Divorced Women

VARIABLES	Divorced Women (No Child) VIF	Divorced Women (1 Child) VIF	Divorced Women (2 Children) VIF	Divorced Women (3 Children) VIF	Divorced Women (4 Children) VIF
interaction	3.06	3.06	3.05	3.05	3.05
treatment	2.44	2.44	2.44	2.44	2.44
yeardummy	1.59	1.59	1.59	1.59	1.59
Mean VIF	2.36	2.36	2.36	2.36	2.36

Table 58: VIFS for Married Men

VARIABLES	Married Men (No Child) VIF	Married Men (1 Child) VIF	Married Men (2 Children) VIF	Married Men (3 Children) VIF	Married Men (4 Children) VIF
interaction	3.06	3.05	3.05	3.05	3.05
treatment	2.44	2.44	2.44	2.44	2.44
yeardummy	1.59	1.59	1.59	1.59	1.59
Mean VIF	2.36	2.36	2.36	2.36	2.36

Table 59: VIFS for Married Women

VARIABLES	Married Women (No Child) VIF	Married Women (1 Child) VIF	Married Women (2 Children) VIF	Married Women (3 Children) VIF	Married Women (4 Children) VIF
interaction	3.06	3.05	3.05	3.05	3.05
treatment	2.44	2.43	2.43	2.43	2.43
yeardummy	1.59	1.59	1.59	1.59	1.59
Mean VIF	2.36	2.36	2.36	2.36	2.36

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