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The effectiveness of German minimum wage policies in reducing the gender pay gap

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Abstract:

The assumption that women would disproportionately benefit from minimum wage reforms stems from their prevalence at the bottom of the wage distribution. However, the qualitative effect of minimum wage raises on men and women individually has been poorly understood. This thesis employs the quasi-experimental method of difference-in-differences and data from the large longitudinal Socio-economic panel (SOEP) to test observable implications of minimum wage policies implemented between 2015 and 2020 on gender wage discrepancies in Germany. The findings show that the qualitative effect of the minimum wage on male and female wages differ. Male wages benefit more from minimum wage increases than women over the 5 year study period. Hence, the findings of this paper suggests that gender pay gap reducing effects attributed to minimum wage policies do not stem from the qualitative effect on improving the labour market outcome of women in terms of wages.

Table of Contents

1. Introduction

The minimum wage policy debate revolves around the trade-off between distributive and allocative efficiency (Berger et al., 2022). Introducing or raising a floor to the price of labour redistributes income from top to bottom but reduces the productivity of a unit of labour. In reality, policy decisions on minimum wage not only redistribute income from the rich to the poor, but also from majorities to minorities, from surplus to shortage, from privileged to disadvantaged. So as well from men to women due to the overrepresentation of women in the low wage sector and at the bottom of the wage distribution (Kahn, 2015; Tucker & Patrick, 2017). Thus, the redistributive effects of minimum wage reforms have the potential to reduce the existing gender distortion in the labour market. Germany has one of the highest gender pay gaps[1] (GPG) in the EU with 18% in 2022. Improved labour market outcomes for women would in turn improve allocative efficiency in the economy through higher labour productivity and thus economic growth. Has the introduction of the minimum wage and subsequent minimum wage policies of raising the level had a lasting effect on the earnings inequality between men and women?

The core argument of this thesis is that raising the minimum wage (MW) does not have an overall gender pay gap reducing effect. This is because two mechanisms affect the GPG in different directions: raising the minimum wage reduces gender wage differentials on the aggregate level as women are more likely to be affected by minimum wage policies in the first place. Yet men who benefit from minimum wage policies do so to a larger extent than women, therefore reducing relative upward mobility of women on the individual level. This is due to the substitution effects between income and leisure that incentivise part-time employment and disincentives the outsourcing of childcare.

One fundamental objective of the minimum wage policy is the redistribution of income. The prevalence of women at the bottom of the wage distribution leads to the assumption that women would disproportionately benefit from minimum wage reforms. Therefore, minimum wage policies could help reduce the gender pay gap among low wage workers. Bargain et al.

[1] In this paper I always refer to the unadjusted gender pay gap, if not explicitly stated differently. The unadjusted GPG is defined as the difference between average gross hourly earnings of men and women in general, without adjusting for pay-related conditions.

(2019) find that minimum wage introduction contributes to narrowing the gender wage gap for low-wage workers in Ireland. Caliendo and Wittbrodt (2021) also find a reducing effect on gender wage disparities following the minimum wage introduction for Germany in the short term. This negative relationship between the minimum wage introduction and the gender pay gap has been established in several studies for Germany[2]. Germany has been a prominent example for this kind of research, due to its relatively recent introduction of the minimum wage in 2015. However, to my knowledge there are no studies analysing the effect of subsequent minimum wage raises in years following the initial introduction. For Poland minimum wage increases have been found to reduce the gender pay gap especially for young workers (Majchrowska & Strawinski, 2018). Hallward-Driemeier et al. (2017) find opposing effects for Indonesia. While the gender pay gap among the least educated exacerbated, educated worker's wage differences reduced. Given these competing mechanisms, the question remains whether minimum wage policies are an effective tool to reduce the gender pay gap, after the imposed initial negative effect shortly after the introduction found in previous research.

The opportunity of reduced working hours has been found to have a positive effect on female labour force participation (Euwals & Hogerbrugge, 2006; Booth & Van Ours, 2013). However, lower average weekly working hours of women compared to men sustains the gender pay gap (Blau & Khan, 2017). Thus, the efficiency of minimum wage policies in reducing the gender pay gap in the long term depends on its impact on the number of working hours. According to economic theory, the labour effect of higher minimum wages can push in two opposing directions. Assuming labour and leisure are normal goods, higher wages might lead to increased labour supply and less leisure time. The substitution effect then causes leisure to be substituted by labour to profit from higher wages and thus higher income. On the other hand, a dominating income effect implies reduced labour supply due to higher demand for leisure in response to the increased income. Thus, a minimum wage reform can incentivize individuals to adapt their working hours according to their preferences. Neumark and Wascher (2008) find that earnings for low-wage workers in the U.S. on average decline following a minimum wage raise despite the initial wage increase as the reduction in hours is larger. Similarly, Caliendo et al. (2017) find for the German minimum wage introduction in 2015 a positive effect at the bottom of the wage distribution, but a negative relationship

[2]see for example Burauel et al. (2018) and Ohlert (2018).

between minimum wage introduction and contractual working hours in the short run. Thus, the efficiency of minimum wage policies in reducing the gender pay gap in the long term depends on the dominance of the substitution effect relative to the income effect. My research adds to the existing literature by estimating the effect on working hours of the MW introduction in 2015, as well as the medium term impact of three subsequent MW level raises and their overall effect on gender wage difference in Germany.

Reduced working hours of women are found to be motivated by care responsibilities for children. Even though some shifts can be seen, care responsibilities remain predominantly in the hands of women and transition is slow despite political efforts[3]. Especially in countries like Germany, where the male breadwinner model has been the central paradigm in society (Lang & Groß, 2020). Goldin et al. (2017) find that wage differences between males and females are largest seven years after schooling ends for the U.S. Statistically, this coincides with the point in time of starting a family. In line with this finding Cukrowska-Torzewska & Matysiak (2020) find that mothers receive lower wages relative to comparable childless women. The identified underlying reason is the loss of human capital of the mother during child-related career breaks. Vuri (2016) finds that making use of external childcare services reduces child-related career breaks and increases labour market participation particularly of women as the main caregiver. However, less attention has been paid to the impact of minimum wage raises on childcare outsourcing for low-skilled workers. The care sector is typically a low-wage female-dominated sector. Thus, costs for child-care outsourcing is likely to increase with higher minimum wages (Rendon, 2023). Hence, increasing the minimum wage might disincentivize mothers to outsource child care due to higher costs and thus female labour market participation does not grow.

My main results show that on the individual level women benefit proportionately less from MW policies than men. While I find positive net effects on wages and working hours over the five year period for both genders, the effects appear to be larger for men than for women. This finding suggests that minimum wage policies do not necessarily improve the labour market outcomes of women relative to men. The positive effect found in past research might be solely attributable to the higher number of women affected by MW policies. Hence, a reduction in the gender pay gap could be observed after the implementation of the minimum

[3] For example the German parental leave policy introduced in 2007, which improves the economic situation for working women on maternity leave and offers incentives for fathers to take paternity leave (Bünning, 2015).

wage in Germany and subsequent raises. However, the single direct effect appears to be larger for men than for women. This would mean that MW policies reduce the gender pay gap only so long as the number of women outnumbers the number of men affected by the policy.

This paper is structured as follows. Section 2 describes the policy background of the German minimum wage and the implemented policy changes during the study period. Section 3 outlines the research design I employ for this study and describes my methodological approach to study the effects of four MW policies on the gender pay gap. Section 4 describes the data, including information on how I chose the working sample and the creation of the core variables used. Section 5 provides descriptive statistics on the working sample as well as on treatment and control groups. In section 6 the estimation results are presented, which is followed by a robustness test in section 7. Section 8 discusses and concludes my findings.

2. Policy Background

The German minimum wage was first introduced in 2015 and stipulates the payfloor for almost all employees of full age. Those in training, long term unemployed within the first 6 months after re-entry in the labour market, employees with disabilities working in accredited workshops and employees participating in employment promotion measures by the Federal Employment Agency are exempt from this pay floor. The set minimum wage level is not regularly adjusted i.e. indexed to inflation, but instead the minimum wage commission advises the government on minimum wage level policies on demand.

In my analysis I exploit these variations in timing and extent of minimum wage adjustments in the period of 2015 to 2020. At the beginning of 2015 Germany introduced its first minimum wage at 8.50€ per hour. The introduction was followed by three minimum wage raises in 2017, 2019 and 2020 which increased the minimum wage level to 8.84€, 9.19€ and 9.35€ respectively. The large repeated cross sectional structure of the employed SOEP data allows me to identify multiple treatment groups depending on the point of time of treatment. Thus, I can estimate the average treatment effect on the treated individuals of a particular group g at time period t. This allows me to observe the average effect of each MW policy and how it evolves over time for each specific group.

3. Methodological Approach

3.1 Research Design

In this study, I follow a difference-in-differences (DiD) research design with multiple time periods that exploits the timing minimum wage reforms that force employers to adjust wages of some workers but not others. Under the key identification assumptions of parallel trends and no treatment anticipation, I identify an average treatment effect on the treated (ATT) of minimum wage policies on wages, economic mobility and child-care outsourcing. In my analysis I validate my core hypothesis that the introduction and subsequent increases of the minimum wage level between 2015 and 2020 have a reducing effect on the gender pay gap and an enhancing effect on the economic mobility in terms of income of women in Germany. To that end, I analyse heterogeneity in ATTs between male and female economic actors. The parallel trends assumption requires that in absence of the minimum wage, the difference between the outcome variables (e.g. working hours) of those treated by the policy and those not treated is constant over time. Moreover, the no treatment anticipation assumption stipulates that neither the minimum wage introduction nor subsequent minimum wage increases have a causal effect prior to their implementation. Furthermore, the consistency assumption and Stable Unit Treatment Value Assumption must hold, which require that the composition of treatment and control groups do not vary over time and that there are no spillover effects between the treatment and control group.

3.2 Methodology

The method I employ differs from the classical approach to DiD in order to accommodate that subjects of my study receive treatment at different points in time depending on the binding character of the newly implemented minimum wage level at that time. Further, in order to estimate the causal effect of these minimum wage changes on the gender pay gap in Germany, I analyse treatment effect heterogeneity across stated gender of the subjects of my study and timing of the policy interventions.

The classic approach to estimate the causal effect would be to control for group and time differences using a (dynamic) two-way fixed effects DiD estimator. However, the staggered treatment timing in my set up in which treatment is applied at different times to differing groups imposes a problem to the statistical validity underlying assumption of fixed effects. There are several before-after periods for various groups and times. Thus, already treated individuals in one period would be used as untreated in another period. This violates the main assumption of the fixed effects method that demands all variables, observed or not, stay constant within a category, here treatment or control group. Callaway and Saint'Anna (2021) offer a solution to this problem by using the staggered treatment assumption that states that every individual who has been once treated remains in the treatment group for all following periods (Irreversibility of treatment).

In order to estimate the effect of the four minimum wage policies I fit the the following potential outcome framework:

$$Y_{i,t} = Y_{i,t}(0) + \sum_{g}^{\tau}(Y_{i,t}(g) - Y_{i,t}(0)) \cdot G_{i,g} \qquad (1)$$

where $Y_{i,t}(0)$ denotes individual i’s untreated potential outcome at time t. For those who do not get treated in any time period, observed outcomes are untreated potential outcomes in all periods. $Y_{i,t}(g)$ denotes the potential outcome of individual i at time t if they first become treated in period g. Under the irreversibility of treatment assumption G defines the treatment group the eventually treated individual belongs to, depending on the time of treatment.

Furthermore, following Callaway and Sant'Anna’s (2021) approach with multiple time periods I consider each group-time treatment effect separately and estimate the average treatment effect on a certain group g for each time period t. This expression is called the group-time average treatment effect:

$$ATT(g,t) = E[Y_t(g) - Y_t(0) | G_g = 1] \qquad (2)$$

I define the never-treated, those who are theoretically MW eligible but not treated by the minimum wage policy at any point in time, as the control group. To compare the group-time treatment effect estimates I use propensity score matching (Callaway & Sant'Anna, 2021). I compare the post-treatment outcomes of the treated group to the outcomes of the most similar never-treated group at each treatment time to estimate each group-time effect. This approach has three key advantages over previous approaches to DiD with treatments in multiple time periods: it allows the researcher to estimate how treatment effects evolve over time, aggregates estimated effects on different levels and relaxes the parallel trends assumption in so far as it places fewer restrictions on the evolution of the outcome variable in the pre-treatment periods. For example, group fixed effects control for any differences between treated and untreated groups that are constant over time.

There are constraints of the classical DiD approach that this approach does not solve either. Predominantly, it does not account for selection factors into treatment that can potentially confound the causal estimand of interest. I solve this problem by choosing a set of control variables that potentially co-determine whether a subject receives treatment and the outcomes of interest. These covariates include information on age, education, migrational background, relationship status as well as the number of children. All these factors can explain both whether a subject can benefit from minimum wage policy and economic outcomes after policy intervention. Given this approach, the parallel trends assumption turns into a conditional parallel trends assumption: conditional on covariates, the average outcomes for the group first treated in a certain period and for the never treated control group would have followed parallel trends in the absence of the treatment. In addition, propensity score matching requires the overlap condition to be met. This condition states that for each treated individual with certain observable characteristics there are at least some untreated individuals in the sample population with the same set of characteristics. As you can find in Table A.1 in the appendix, my sample contains a substantial number of subjects who never received treatment in the time-frame of this study. As expected, there are several covariates that show systematic differences between those who never benefited from minimum wage reform and those who do. Notably, being unmarried, divorced, not having a spouse and no high-school degree as well as a migration background makes subjects more likely to benefit from minimum wage reforms. Although, this can potentially indicate a treatment selection mechanism based on unobserved or unobservable confounders, the propensity score matching approach I employ in this paper ensures that as long these confounders correlate with the covariates I condition for, the estimates I present in this paper are unbiased.

I make use of doubly-robust DiD estimators based on stabilised inverse probability weighting and ordinary least squares developed by Sant'Anna and Zhao (2020). Double robustness allows the identification of the ATT even if one of the working nuisance models, propensity score matching or the outcome regression model is not correctly specified. To account for autocorrelation I employ wild bootstrapped standard errors.

4. Data

The repeated cross-sectional data I rely on for my research comes from the Socio-Economic Panel (SOEP). The SOEP is an annual household survey of a representative sample of Germany's residential population. The longitudinal study gathers information on wide-ranging topics such as household composition, employment, earnings and satisfaction indicators of about 28,000 individuals in about 16,000 households per year (Siegers et al., 2022). Interviewers try to obtain face-to-face interviews with all members of a given survey household aged 16 and older and one household member ("head of household") completes the questionnaire on the household including questions on housing as well as children up to the age of 16 in the household. My estimations are based on the SOEP v37 version, which includes individual-level data from the first survey year 1984 up to 2020. In my analysis I consider data from the years 2013 to 2020.

4.1 Working sample

The population of interest for my research question is made up of employees who are theoretically eligible for the minimum wage in Germany. Therefore, those not minimum wage eligible according to the regulations stated in section 2 on *Policy background* are exempted as far as the data on the individual permits identification. Furthermore, the working sample only includes respondents for which income data as well as information on working hours is available. To prevent the distortion of outliers, the monthly labour income data is winsorized by setting the top and bottom 1 percent of earnings to the value of the first and 99th percentiles, respectively. By limiting the data adjustments to a minimum I aim to preserve the representative character of the data.

Table 1 presents the division of the full SOEP sample into minimum wage eligibles and Non-minimum wage eligibles based on the imposed restrictions. Furthermore, while only respondents with information on labour earnings and working hours are included in the MW eligible sample, the Non-MW eligible group is made up of identified non-eligible as well as those with missing information on these variables. After all restrictions my working sample population of MW eligibles includes 25% of the total SOEP population between 2013 and 2020 which adds up to a headcount of 114,231 individuals.

Table 1: Division of the sample between 2013 and 2020 into minimum wage eligible and non-eligible based on policy regulations as well as data restrictions. The minimum wage eligible make up the working sample population for the analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full sample	2013	2014	2015	2016	2017	2018	2019	2020
MW eligible	0.25	0.28	0.27	0.28	0.23	0.23	0.23	0.23	0.24
	(0.432)	(0.452)	(0.446)	(0.448)	(0.419)	(0.422)	(0.423)	(0.418)	(0.426)
N	467796	55611	51684	50277	57287	64554	62491	62829	63063

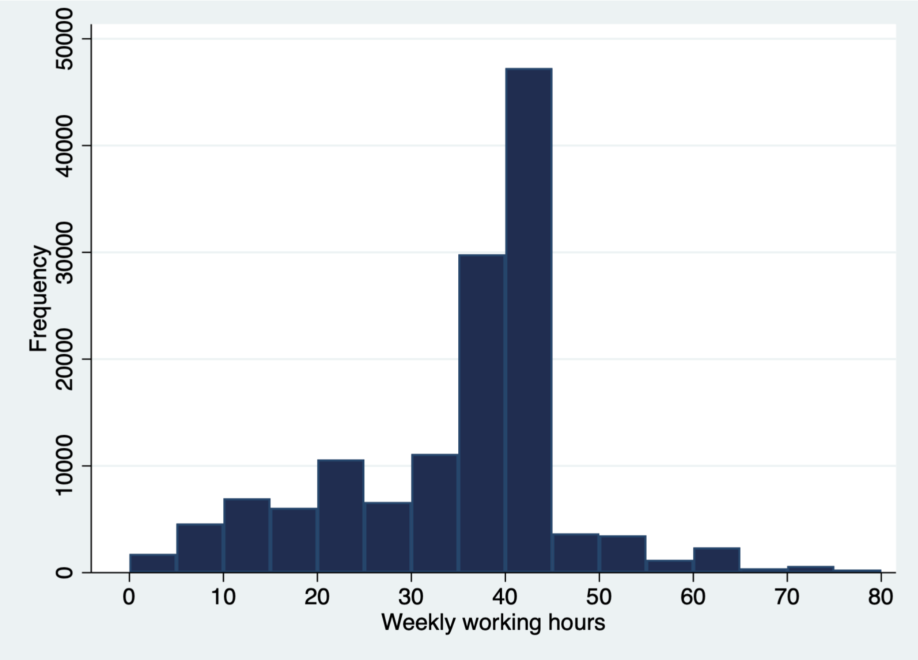
mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP v37, own calculations.

4.2 Core variables

4.2.1 Working hours

The SOEP includes two different variables on working hours: contractual working hours and actual working hours. I employ contractual working hours if available, because this is the number of hours the wage is agreed upon. The actual working hours are employed, if information on contractual working hours is not available. This is done to make use of as many respondents and thus as much information as possible. As a robustness test, I estimate results using contractual working hours only in section 7. The corresponding results do not significantly deviate from my findings.

Graph 1: Working hours per week of the full working sample population



Source: SOEP v37, own calculations.

4.2.2 Part-time Employment

Full- and part-time employment are no universally defined concepts. The Institute of International Labor Organization defines a part-time employee as a person whose normal working time is less than that of those in a comparable full-time position (Hill, 2015). This definition leaves scope for interpretation in statistical analyses. In the following analysis I follow the definition of the OECD that defines part-time employment as less than 30 working hours per week in their main job, and at least 30 hours per week as full-time employment (OECD, 2023).

Table 2: Characteristics of the full working sample population over the entire study period 2013 to 2020 and for each year separately.

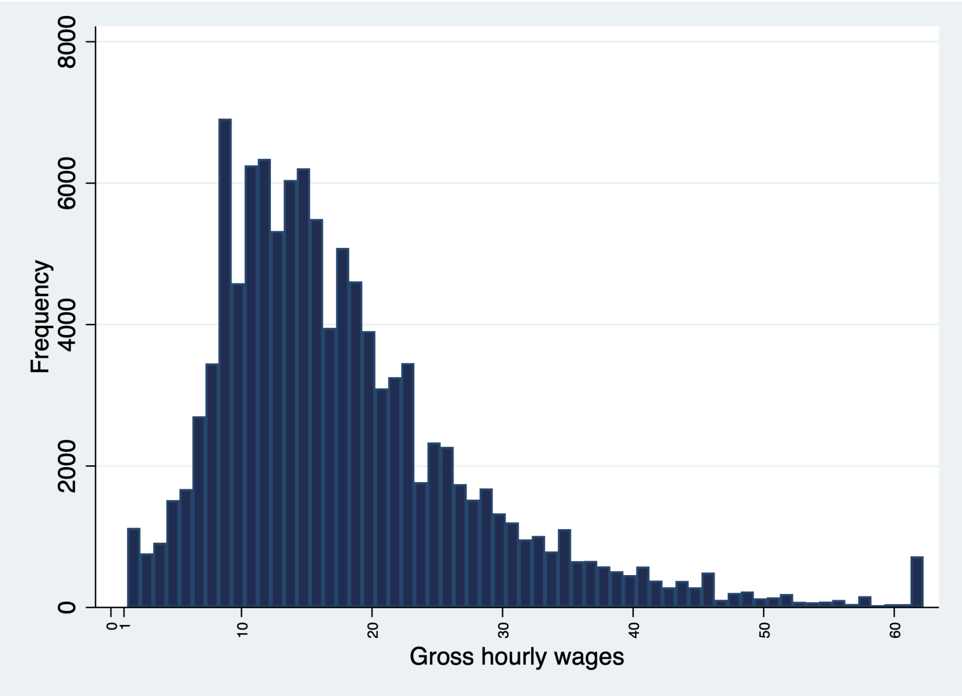
	(1) Full working sample	(2) 2013	(3) 2014	(4) 2015	(5) 2016	(6) 2017	(7) 2018	(8) 2019	(9) 2020
Average working hours per week	32.04 (12.34)	32.15 (12.25)	32.11 (12.12)	32.25 (12.16)	31.62 (12.65)	31.79 (12.57)	31.91 (12.14)	32.10 (12.36)	32.33 (12.49)
Full-time employed	0.70 (0.459)	0.70 (0.460)	0.69 (0.461)	0.70 (0.459)	0.69 (0.464)	0.69 (0.462)	0.69 (0.461)	0.70 (0.459)	0.72 (0.449)
Full-time employed males	0.44 (0.496)	0.45 (0.497)	0.44 (0.497)	0.44 (0.497)	0.42 (0.494)	0.43 (0.496)	0.43 (0.496)	0.44 (0.496)	0.45 (0.498)
Full-time employed females	0.26 (0.437)	0.25 (0.432)	0.25 (0.434)	0.25 (0.435)	0.26 (0.440)	0.26 (0.437)	0.26 (0.439)	0.26 (0.439)	0.27 (0.443)
Part-time employed	0.28 (0.451)	0.29 (0.456)	0.30 (0.458)	0.29 (0.454)	0.29 (0.452)	0.28 (0.451)	0.29 (0.453)	0.28 (0.451)	0.24 (0.429)
Part-time employed males	0.05 (0.213)	0.04 (0.196)	0.04 (0.203)	0.04 (0.201)	0.04 (0.204)	0.05 (0.213)	0.06 (0.235)	0.06 (0.235)	0.05 (0.216)
Part-time employed females	0.24 (0.424)	0.25 (0.436)	0.26 (0.436)	0.25 (0.431)	0.24 (0.429)	0.24 (0.425)	0.23 (0.420)	0.22 (0.417)	0.19 (0.395)
N	114231	15755	13985	13813	12841	14724	14391	13937	14785

mean coefficients; sd in parentheses
Source: SOEP v37, own calculations.

4.2.3 Hourly wages

The SOEP does not include a variable on hourly wages, but it provides sufficient data to construct a corresponding variable. I used the information on the gross labour income per month from the main employer and the number of working hours per week to calculate gross hourly wages of each respondent.

Graph 2: Gross hourly wages per week of the entire working population over the study time period 2013 to 2020.



Source: SOEP v37, own calculations.

4.2.4 Economic Mobility

Economic mobility here refers to the intragenerational mobility of an individual within the study period. It measures the movement of an individual across the income distribution. I split the monthly labour earnings of individuals in 2014 into quintiles. Thus, the boundaries of each quintile in 2014 serve as reference for the following years whether one individual has moved one or more quintiles from one year to the next. Economic mobility can be measured for about 64% of the sample, because income data on consecutive years must be available for an individual. Table 3 shows the economic mobility pattern of respondents between 2013 and 2020.

Table 3: Economic Mobility measured in terms of movement across quintiles from one year to the next

Quintile movement	Survey year							
	2014	2015	2016	2017	2018	2019	2020	Total
-4	6	3	6	9	7	5	10	46
-3	12	12	19	16	21	20	21	121
-2	85	64	62	66	59	66	96	498
-1	747	681	656	657	715	608	723	4787
0	8970	8284	8049	7486	8482	7905	7771	56947
1	1592	1398	1420	1365	1610	1558	1440	10383
2	158	127	141	136	153	181	150	1046
3	26	20	32	37	43	40	38	236
4	5	4	12	12	10	12	9	64
Total	11601	10593	10397	9784	11100	10395	10258	74128

Source: SOEP v37, own calculations.

4.2.5 Childcare outsourcing

The hours per week parents make use of external childcaring services per child is measured using provided information on the number of children with respective age. In addition I employ information from various questions on the options of caretaking and the respective time parents make use of these services per week. I only take children under the age of 12 into account, as I assume these kids are always in need of caretaking. The final variable measures the average hours per week the child spends with an external caregiver[4].

Table 4: Hours of outsourced childcare per week of a child under 12

Hours of outsourced childcare per week	Survey year							
	2014	2015	2016	2017	2018	2019	2020	Total
0	841	936	948	894	923	669	694	5905
1-5	98	66	69	75	80	93	76	557
5-10	89	87	91	78	82	92	50	569
10-15	82	87	62	74	84	64	47	500
15-20	75	78	74	69	76	72	60	504
20-25	95	87	92	71	77	53	59	534
25-30	74	56	44	40	42	23	39	318
30-35	68	67	55	38	54	42	56	380
35 or more	158	138	156	86	103	99	89	829
Total	1580	1602	1591	1425	1521	1207	1170	10096

Source: SOEP v37, own calculations.

[4] I consider external and most likely fee-required care facilities such as creches, nurseries, after-school childcare, social institutions and external babysitters. Not considered child care outsourcing is caretaking by relatives or friends.

5. Descriptive Statistics

Whether an individual experiences treatment or not depends on the binding of the minimum wage level set at each policy intervention. Thereby, the treatment group can be divided into different sub treatment groups depending on their timing of treatment. Due to the staggered treatment assumption the treatment group of the last period includes all treated individuals from every period. On the same grounds, individuals treated in period one would be always treated. The always treated would be excluded from analysis because their untreated potential outcomes are never observed and thus corresponding treatment effects cannot be identified, nor are these individuals useful as a comparison group under the parallel trends assumption. In order to avoid loss of information I have included survey data from 2013, so untreated potential outcomes can be observed for every individual, also the units treated in the first treatment period 2015. Moreover, the inclusion of data two years prior to the first treatment provides information on pre-treatment trends to inspect whether the parallel trends assumption holds.

Table 5: Characteristics of the full working sample as well as on each treatment group and the control group of never treated individuals.

	(1) Full working sample	(2) Treatment Group 2015	(3) Treatment Group 2017	(4) Treatment Group 2019	(5) Treatment Group 2020	(6) Control Group
Proportion male	0.50	0.26	0.29	0.31	0.32	0.53
	(0.500)	(0.441)	(0.454)	(0.462)	(0.466)	(0.499)
Average age in years	43.20	43.74	43.20	42.50	42.12	43.38
	(11.57)	(12.22)	(12.34)	(12.62)	(12.68)	(11.37)
Males average age in years	42.93	41.68	41.62	40.37	39.91	43.23
	(11.69)	(13.64)	(13.59)	(13.64)	(13.58)	(11.44)
Female average age in years	43.48	44.48	43.85	43.45	43.16	43.55
	(11.44)	(11.58)	(11.73)	(12.01)	(12.10)	(11.28)
Average weekly working hours	32.68	25.51	25.56	25.41	25.56	33.84
	(11.60)	(13.34)	(13.50)	(13.67)	(13.75)	(10.78)
Male average weekly working hours	37.60	33.41	32.98	32.31	32.35	38.12
	(8.976)	(13.88)	(13.79)	(14.04)	(14.13)	(8.119)

Female average weekly working hours	27.80 (11.85)	22.69 (11.94)	22.55 (12.15)	22.35 (12.32)	22.42 (12.37)	29.07 (11.35)
Gross hourly wages	18.04 (10.30)	9.34 (5.021)	9.56 (5.243)	9.55 (5.268)	9.62 (5.396)	19.42 (10.26)
Male gross hourly wages	20.09 (11.15)	9.77 (5.590)	9.97 (5.799)	9.94 (5.949)	9.98 (6.015)	21.08 (11.05)
Female gross hourly wages	16.02 (8.933)	9.18 (4.793)	9.40 (4.990)	9.38 (4.926)	9.46 (5.077)	17.58 (8.942)
N	114231	7323	11238	14331	16029	98202

mean coefficients; sd in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEP v37, own calculations.

Table 5 presents information on characteristics of the full working sample as well as each treatment group, depending on the timing of treatment and the control group of the never treated individuals, who earn wages higher than the relative minimum wage in every period. The working sample population and the control group consists equally of men and women. However, an overrepresentation of women can be observed among the treated. In 2015 74% of those affected by the minimum wage introduction were female, which is in accordance with the actual fraction of women affected in the German population (Mindestlohnkommission, 2016b; Burauel et al., 2017). By design, those treated earn significantly less on average per hour than those not affected by minimum wage policies. Moreover, while the average hours of a working week consists of about 33 hours for the full population sample and the control group, the treatment groups work about 6 hours less throughout the 5 year period. Across all groups, we can furthermore observe a remarkable difference between men and women in terms of working hours. Women's average labour participation is about 10 hours less per week than men's in every year. Additionally, women earn considerably less than men per hour and even in the treatment groups a wage difference is apparent. For the full population sample the data shows an hourly earnings difference of almost 4€. The wage gap in the control group is slightly smaller with a 3.50€ wage difference between men and women per hour. The smaller wage gap in the control group compared to the full working sample is likely to be due to the large proportion of low waged women found in the treatment groups, rather than in the control group.

Table 6 shows the gender pay gaps for every year between 2013 and 2020 of the full working sample population of minimum wage eligible respondents. The GPG is measured as the difference between the average gross hourly wages of male and female employees relative to the average gross hourly wages of male employees. For the two years prior to the introduction of the MW reform in 2015 a steady GPG of 25% can be observed. After the MW introduction the GPG continuously declined, with a significant drop between 2016 and 2017 of 3 percentage points for the working sample population. This coincides with the first MW level increase in 2017 of 0.34€, from 8.50€ to 8.84€. In the following years the GPG continued to decline steadily for the sample.

Table 6 : Gender Pay Gap of the working sample population between 2013 and 2020.

	(1) 2013	(2) 2014	(3) 2015	(4) 2016	(5) 2017	(6) 2018	(7) 2019	(8) 2020
Gender Pay Gap (GPG)	0.25	0.25	0.23	0.22	0.19	0.17	0.16	0.15
N	15755	13985	13813	12841	14724	14391	13937	14785

Source: SOEP v37, own calculations.

6. Results

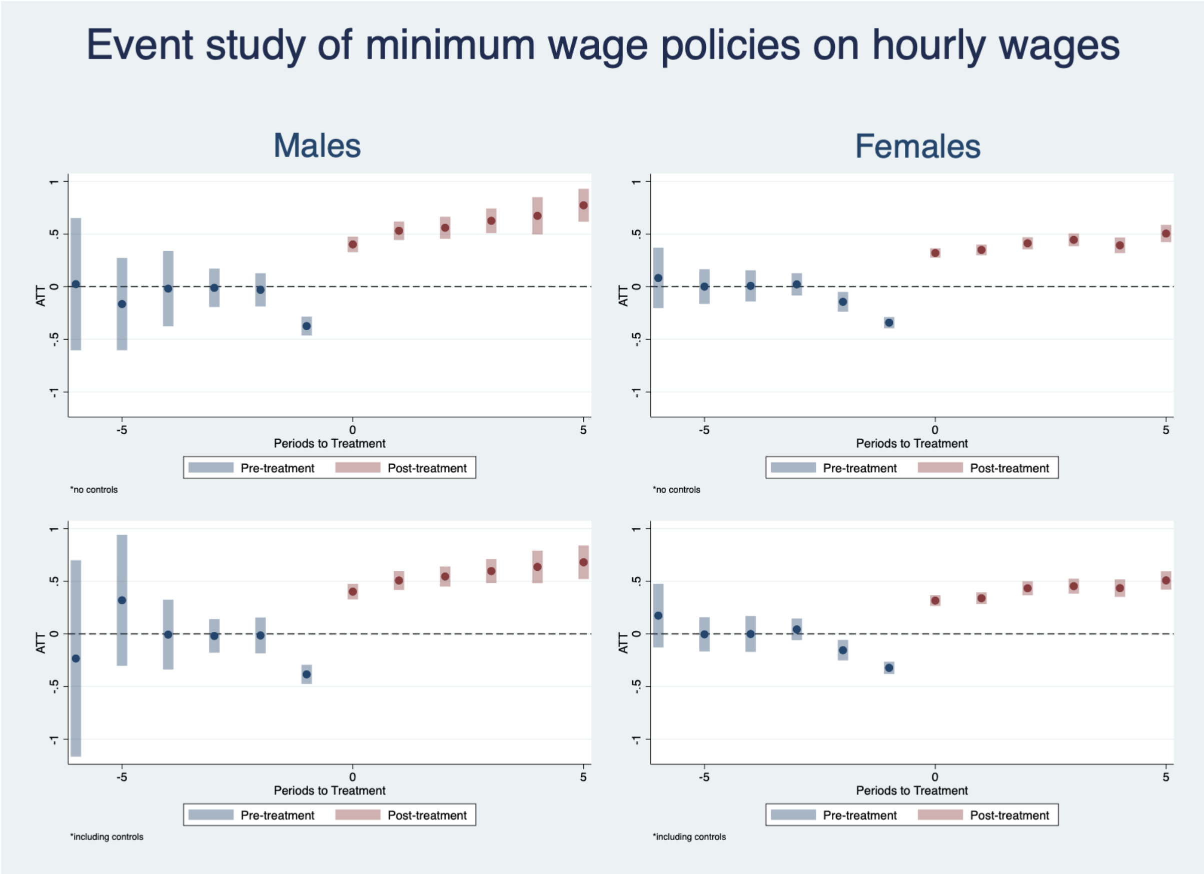
My results are separated into five different sets of outcomes: the effect of the MW policies of 2015, 2017, 2019 and 2020 in Germany on hourly wages, economic mobility, working hours, part-time employment and outsourcing childcare. The effects are measured for men and women separately to compare the findings on each gender. For every outcome I present two different sets of results on aggregated group-time average treatment effects. One, in which I assume the parallel trends assumption holds unconditionally, and one conditional on observed characteristics on age, education, migrational background, relationship status and the number of children living at home. The *simple* aggregation returns a weighted average over all group-time treatment effects with group size proportional weights. The *calendar* aggregation estimates the average effect of participating in the treatment in a particular time-period for all groups that are treated in that time period. The *group* aggregation estimates group-specific treatment effects averaged across all time periods in which the particular group has been treated. As a fourth aggregation the group-time average treatment effects are averaged into treatment effects with respect to their length of exposure to the treatment. The estimation results of the dynamic *event* aggregations are plotted for every regression result in graphs 3 to 8 below. The event study plots also show trends prior treatment, which show indication of whether the parallel trends assumption holds. All estimation results on the aggregated group-time average treatment effects are reported in Appendix A.

6.1 Hourly wages

I estimate the effect of the newly implemented minimum wage level on the logarithm of wages per hour for men and women separately. Graph 3 presents the aggregate group-time effects averaged into mean treatment effects at different lengths of exposure to the treatment. The left side depicts the event estimation results for the male and the right side for the female population. The pre-trends for both, males and females, suggest that parallel trends assumption might be violated due to significant negative effects in the last period just before the treatment for men and the last two periods for women. For males the chi-squared statistic of $Chi^2(15) = 3.4611$ with a p-value of 0.999 suggests that all pre-trend average group-time average treatment effects are equal to zero. This is in line with the average treatment effect of the event study prior treatment, which is not statistically significant when including controls. Thus, one fails to reject the parallel trends in pre-treatment periods. Minimum wage policies increased average male wages for each treatment group with a point estimate of 66.4% over the 5-year period.

For females it can be observed in Graph 3 that the two periods just before the first treatment period are clearly negative. Thus, there appears to be some evidence against the parallel trends assumption. However, the two concerned pretreatment effects estimate an average decrease of 16.8% pre-period two and 38% in pre-period one of female hourly wages. With the implementation of the minimum wage policy female hourly wages of those affected by the policy immediately increased by a point estimate of 37%. In the forthcoming periods the effect accrues with increasing length to exposure of the treatment. Hence, if there has been a shock prior to treatment, this shock is negative and its effect seems stronger for women than for men. This effect would bias the estimated difference between average effects on male and female wages in a positive direction and thus I argue that my estimates represent a lower bound of the actual effect. I find a slightly larger average post treatment effect on male wages with a point estimate of 75% growth compared to 51% hourly wage growth for women. Moreover, from the results can be inferred that the effect of the minimum wage policies on the treated seem to increase the longer the individuals are exposed to the policy. The finding shows that the MW policies between 2015 and 2020 have an overall positive and statistically significant effect on log hourly wages. The policy is efficient in lifting the bottom of the wage distribution. However, the results also indicate that men's wages increase on average 68% more than women's. Hence, the minimum wage policy might not be effective in reducing the gender pay gap on the individual level.

Graph 3 : Results of the event analysis on hourly wages for men and women separately.



Source: SOEP v37, own calculations.

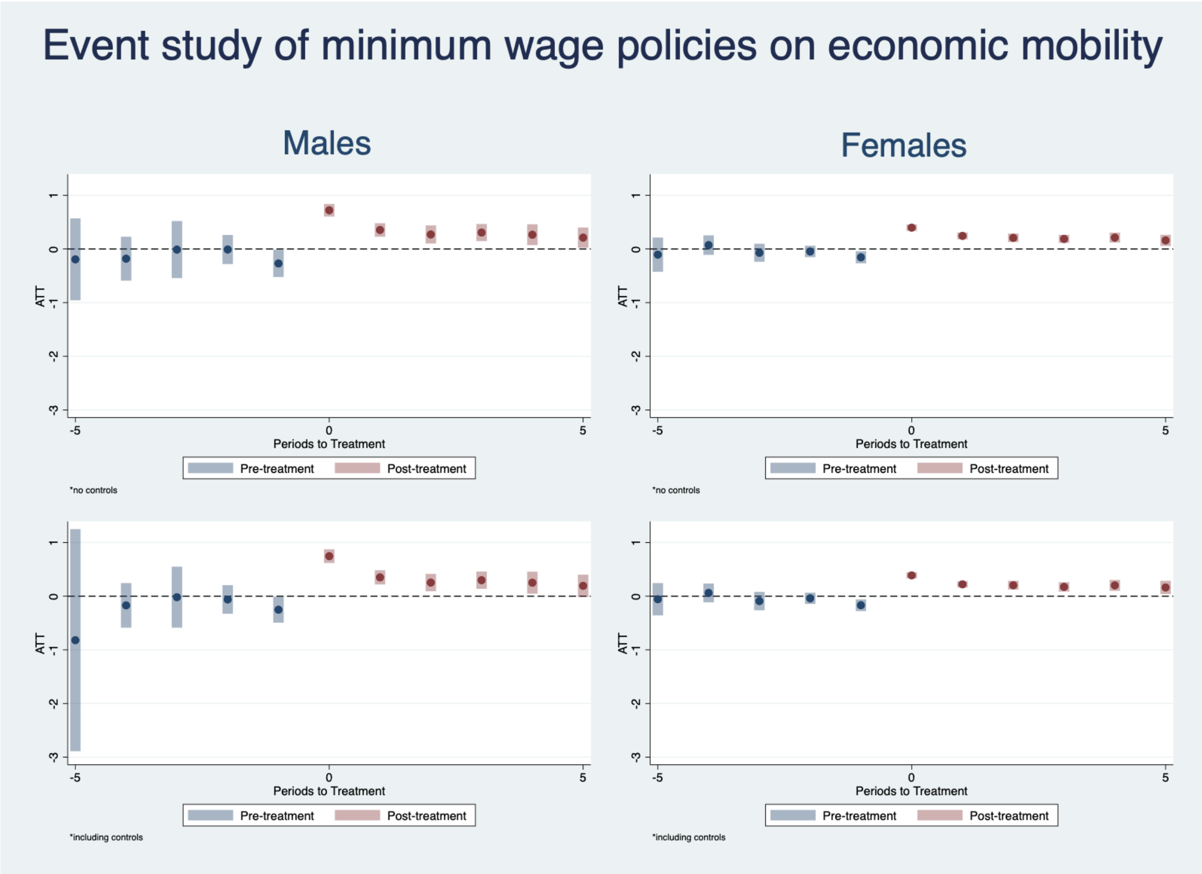
6.2 Economic Mobility

In the analysis of the impact of the minimum wage on the ability of an individual to move along the income distribution, I find positive and statistically significant effects. Graph 3 shows that the instantaneous treatment effect is the greatest. Men's ability to move upwards on the income distribution increases on average about 92% more than womens directly after a MW policy change. A following decline of the average treatment effect can then be observed for both genders. The longer the treated are exposed to the MW policy, the lesser the impact but it remains positive and statistically significant throughout all periods.

However, there is indication for the failure of the parallel trends assumption based on the event study estimation of the pre-trend. As in the case of the effect on hourly wages, a negative shock on the economic mobility right before the first treatment period can be observed. Similarly, I find the negative shock to have a stronger effect on women than on men. The male average pre-trend effect is not significant, thus parallel trends assumption is likely to hold for the men. Women's ability to move across the income distribution is, however, significantly reduced in these two last pre-treatment periods. Again, it appears that the estimated average effect on the economic mobility of the treated form the lower bound of the actual effect.

Every treatment group experiences clearly positive and economically significant improvements on their ability to climb upwards on the income distribution following new minimum wage policy implementations. The group-specific treatment effects thereby confirm the finding of the event study plot that the effect is greatest directly after the policy implementation. This result confirms my expectations. Introducing or raising the MW essentially lifts the lowest wages. Thus, the ability to move towards the second quintile is improved through the policy implementation, which causes the instantaneous peak in the treatment effect. Over time this lifting effect diminishes but remains positive over the observed period. Hence, in the medium term of five years a MW policy seems to have a lasting positive but diminishing effect on economic mobility on those affected by the minimum wage.

Graph 4 : Results of the event analysis on economic mobility



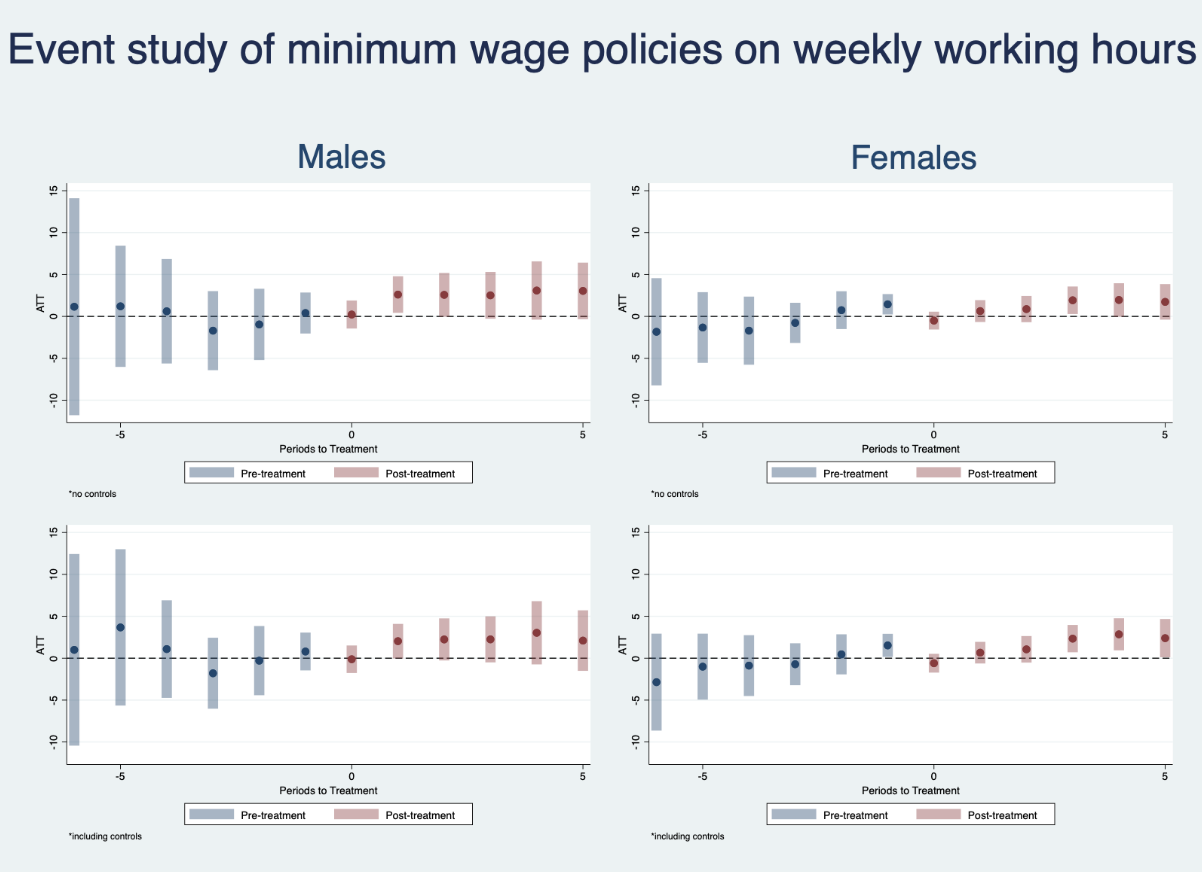
Source: SOEP v37, own calculations.

6.3 Working hours

One mechanism that has been identified to cause the discrepancy between male and female earnings is the difference in working hours. The pre-trend of the event study plot in graph 5 provides no indication that parallel trends assumption does not hold. My findings show a weak positive effect of the minimum wage policies on the number of working hours for men. Yet, a positive trend on the number of working hours can be observed for women as well. The estimated effect on the hours of men spent at work thereby is larger and statistically more relevant than the effect on female working time considering the different aggregation estimates.

From these results, we can see a tendency that the substitution effect is larger than the income effect following MW policies. Thus, the introduction and increase of minimum hourly wages tend to incentivize employees to work slightly more per week. The effect, however, is weak and is unlikely to be powerful enough to reduce the large discrepancy of working hours between men and women.

Graph 5 : Results of the event analysis on working hours

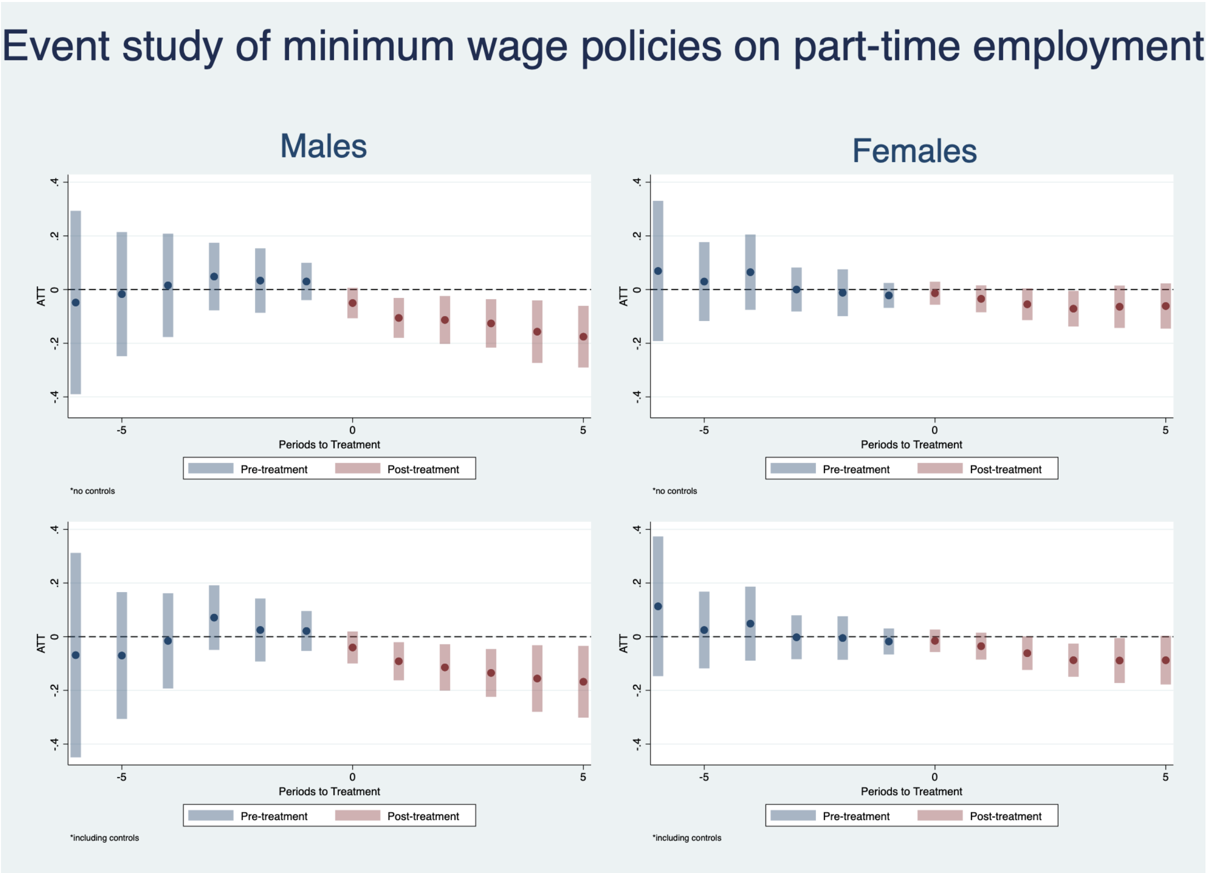


Source: SOEP v37, own calculations.

6.4 Part-time employment

The previous finding of a weak positive effect on the number of working hours is corroborated by the finding of the effect of the MW policies on part-time employment. The event study plot presented in graph 6 shows clearly negative effects on part-time employment. However, the graph also highlights that the effect is more distinct on men than on women. Considering the point estimates of the male event study plots, one can observe an increasing effect on the reduction of part-time employment the longer the treated are exposed to the MW policy. In contrast, the point estimates of the female sample indicate that after the initial decrease in part-time employment, the effect appears to level. Given the initial situation that the proportion of part-time employees is substantially higher among women than men, the effect of MW policy does not seem to effectively reduce this gap.

Graph 6: Results of the event analysis on part-time employment for men and women.

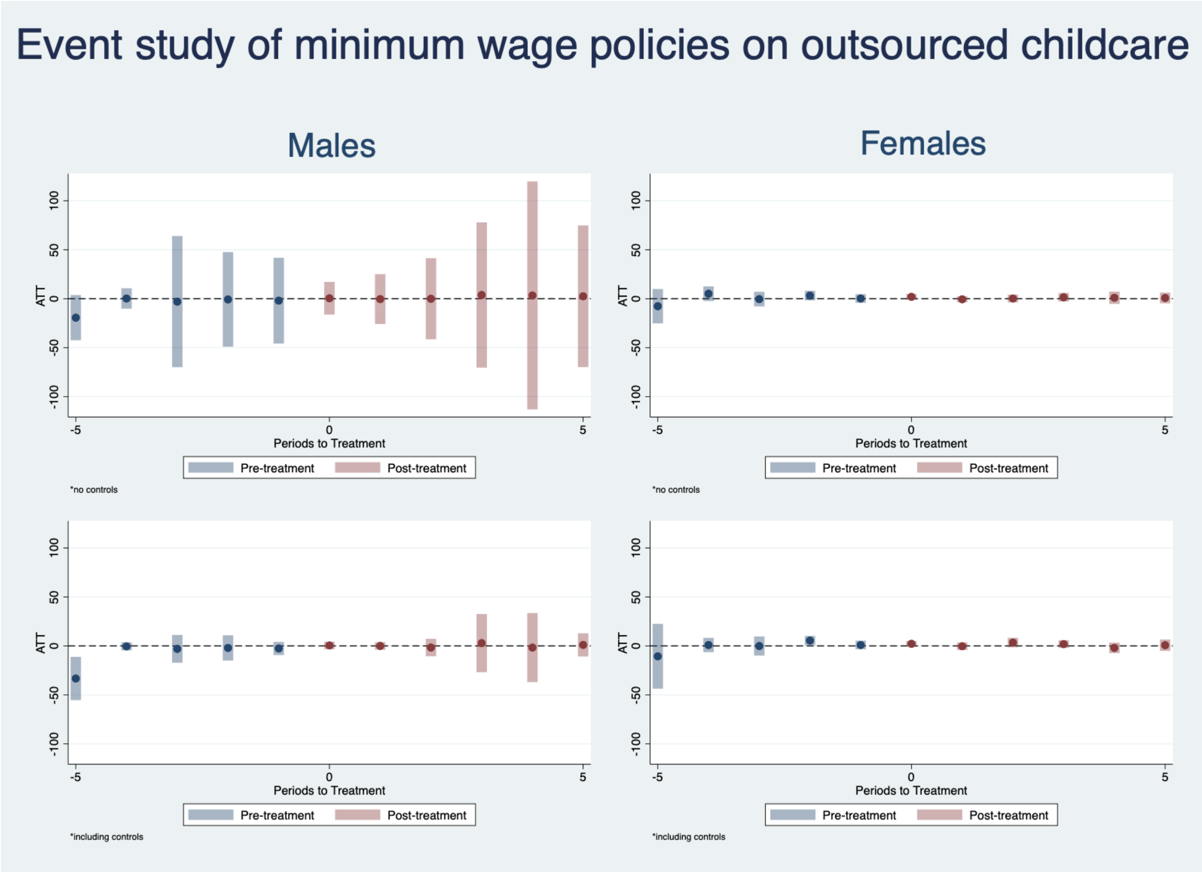


Source: SOEP v37, own calculations.

6.5 Outsourcing of childcare

One possible reason for a weaker effect of the MW on female working hours could be due to relatively higher care responsibilities of mothers. I test whether parents have changed the outsourcing of childcare for children under 12 following MW policies. I find no evidence for an effect of the MW on the number of hours a child spends at an external care-giver. Considering the relatively small positive effect on working hours for women, this absence of an effect on child care outsourcing suggests that mothers continue working less and take care of their young children themselves. Simultaneously, the result neither provides evidence that increasing MW levels have a negative effect on the outsourcing of children, even though the care sector is typically a female dominated low-wage sector and hence likely to be affected by MW policies. I find no reason to believe higher MW policies disincentivize childcare outsourcing through e.g. higher costs due to higher wages of caregivers passed on to consumers.

Graph 7 : Results of the event analysis on childcare outsourcing



Source: SOEP v37, own calculations.

7. Robustness Test

In this research I employ contractual working hours if available and use the number of actual working hours stated by the respondent if the individual does not provide information on the former. However, the number of hours fixed in the employment contract can deviate from the effective working hours a person spends working. Thus, actual working hours include typically overtime hours and the contractual working hours. Whether these overtime hours are compensated for in some form i.e. in form of payments, compensatory time-off or alike is cannot be identified from the data. Since I rely on self-reported information on working hours, there might be a tendency of respondents exaggerating the actual working hours. In order to test whether those only reporting actual working hours and not contractual working hours leads to bias I perform a robustness check in which I perform the DiD analysis including respondents with reported information on contractual working hours only. In Appendix B I report the results of the DiD estimations on log hourly wages and working hours. I find similar results for the robustness test. MW policies appear to also have a larger effect on men than on women, when considering contractual working hours only. However, in absolute terms the effects on working hours and hourly wages deviates. A larger effect is estimated on the number of working hours and a slightly smaller effect on hourly wages when excluding actual working hours. Hence, my results might underestimate the effect on working hours and overestimate the effect on hourly wages. A possible explanation could be that in response to the introduction of a minimum wage unpaid extra hours increase as suggested by Caliendo et al. (2017).

8. Discussion and Conclusion

In summary, this study finds that women, on the individual level, do not benefit more from the minimum wage policies than men. Rather, the positive effects on the labour market outcomes show a tendency to be more pronounced for men than for women. This conclusion is based upon my finding that male hourly wages tend to rise more following a new minimum wage policy implementation than female wages per hour. In addition, I find that the effect of the minimum wage on the ability to move up on the income distribution is also greater for men. Therefore, a man's labour outcome seems to improve more from a minimum wage policy than a woman's. The main identified mechanism that leads to this result, is that men are more incentivized by minimum wage policies to increase their number of working hours. My results show a dominating substitution effect for both men and women. However, I find the effect measurably larger for men. This finding is corroborated by the result that minimum wage policies lead to a more significant negative effect on part-time employment for men than for women. Part-time employees are more likely to earn minimum wage than full-time employees. And the fraction of women working part-time is much larger relative to men. The weaker effect on the increase in working hours and decrease in part-time employment on women compared to men might in turn explain the lesser effect of minimum wage policies on female economic mobility.

In terms of policy implications, my findings offer evidence that minimum wage policies can only reduce the minimum wage gap as long as women are significantly overrepresented at the bottom of the wage distribution. If as intended by gender pay gap reducing policies the minimum wage affected population would become more balanced in the future, the distributive efficacy of minimum wage policies diminishes. Considering the significant difference in estimated effects on genders of 68% on hourly wages the distributive gains arguably become weaker with every minimum wage raise. A possible explanation for the weaker effect on women might be rooted in higher opportunity costs for women to increase working hours and change employment type from part-time to full-time. Blau and Kahn (2007) among others identify higher care responsibilities of women as one reason for fewer female working hours. An increase in the outsourcing of childcare could have a positive effect on working hours. However, I find no indication of an effect of minimum wage on the outsourcing of childcare. Hence, larger care responsibilities of women compared to men might still prevent women from increasing working hours following an increase in wages to the extent that men do. Minimum wage policies treat the symptoms of the gender pay gap - low wages of women. However, on the individual level men benefit more from these policies than women as they respond more to the wage incentives. Future research could investigate the underlying reasons for the less intense response of women on minimum wage policies compared to men. Targeting these causes would improve the efficacy of minimum wage policies in reducing the gender pay gap.

References

Bargain, O., Doorley, K., & Van Kerm, P. (2019). Minimum wages and the gender gap in pay: new evidence from the United Kingdom and Ireland. *Review of Income and Wealth*, *65(3)*, 514-539.

Berger, D. W., Herkenhoff, K. F., & Mongey, S. (2022). Minimum wages, efficiency and welfare (Working Paper No. 29662). *National Bureau of Economic Research*.

Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, *55(3)*, 789-865.

Booth, A. L., & Van Ours, J. C. (2013). Part-time jobs: What women want? *Journal of Population Economics*, *26*, 263-283.

Bünning, M. (2015). What happens after the 'daddy months'? Fathers' involvement in paid work, childcare, and housework after taking parental leave in Germany. *European Sociological Review*, *31(6)*, 738-748.

Burauel, P., Caliendo, M., Fedorets, A., Grabka, M., Schröder, C., Schupp, J., & Wittbrodt, L. (2017). Minimum wage not yet for everyone: on the compensation of eligible workers before and after the minimum wage reform from the perspective of employees. *DIW Economic Bulletin*, *7(49)*, 509-522.

Burauel, P., Grabka, M., Schröder, C., Caliendo, M., Obst, C., & Preuss, M. (2018). Auswirkungen des gesetzlichen Mindestlohns auf die Lohnstruktur, Studie im Auftrag der Mindestlohnkommission, Deutsches Institut für Wirtschaftsforschung. *Evaluation Office Caliendo, Berlin.*

Caliendo, M., Fedorets, A., Preuss, M., Schröder, C., & Wittbrodt, L. (2017). The Short-Term Distributional Effects of the German Minimum Wage Reform. *IZA Discussion Paper*, *No. 11246*.

Caliendo, M., & Wittbrodt, L. (2021). Did the minimum wage reduce the gender wage gap in Germany? (Working Paper No. 40). *Center for Economic Policy Analysis (CEPA)*.

Callaway, B., & Sant'Anna, P. (2021). Difference-in-differences with multiple time periods. *Journal of econometrics*, *225(2)*, 200-230.

Cukrowska-Torzewska, E., & Matysiak, A. (2020). The motherhood wage penalty: A meta-analysis. *Social science research*, *102416*, 88-89.

Euwals, R., & Hogerbrugge, M. (2006). Explaining the growth of part-time employment: Factors of supply and demand. *Labour*, *20(3)*, 533-557.

Goebel, J., Grabka, M., Liebig, S., Kroh, M., Richter, D., Schröder, C., & Schupp, J. (2018). *The German Socio-Economic Panel Study (SOEP)*. Jahrbücher für Nationalökonomie und Statistik / Journal of Economics and Statistics. doi:10.5684/soep.core.v37eu

Goldin, C., Kerr, S. P., Olivetti, C., & Barth, E. (2017). The expanding gender earnings gap: Evidence from the LEHD-2000 census. *American Economic Review*, *107(5)*, 110-114.

Hallward-Driemeier, M., Rijkers, B., & Waxman, A. (2017). Can minimum wages close the gender wage gap? Evidence from Indonesia. *Review of Income and Wealth*, *63(2)*, 310-334.

Hill, S. (2015). Non-standard forms of employment–Report for discussion at the Meeting of Experts on Non-Standard Forms of Employment. *Geneva: ILO*.

Kahn, L. M. (2015). Wage compression and the gender pay gap. *IZA World of Labor*.

Lang, V., & Groß, M. (2020). The just gender pay gap in Germany revisited: The male breadwinner model and regional differences in gender-specific role ascriptions. *Research in Social Stratification and Mobility*, *65*, 100473.

Majchrowska, A., & Strawinski, P. (2018). Impact of minimum wage increase on gender wage gap: Case of Poland. *Economic Modelling*, *70*, 174-185.

Mindestlohnkommission. (2016b). *Stellungnahmen aus der schriftlichen Anhörung. Ergänzungsband zum ersten Bericht der Mindestlohnkommission*. Berlin: Mindestlohnkommission.

Neumark, D., & Wascher, W. L. (2008). Minimum wages. *MIT press*.

OECD. (2023). *Part-time employment rate (indicator)*. Retrieved July 11, 2023, from doi: 10.1787/f2ad596c-en

Ohlert, C. (2018). Gesetzlicher Mindestlohn und der Gender Pay Gap im Niedriglohnbereich: Ergebnisse aus der Verdienststrukturerhebung 2014 und der Verdiensterhebung 2015. *Zeitschrift für amtliche Statistik Berlin Brandenburg*, *2*, 26-31.

Rendon, J. H. (2023). The Effect of Minimum Wage Increases on the Child Care Industry. *American University, School of Public Affairs*. http://dx.doi.org/10.2139/ssrn.4505940

Sant'Anna, P., & Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics*, *219(1)*, 101-122.

Siegers, R., Steinhauer, H. W., & Schütt, J. (2022). SOEP-Core v37 – Documentation of Sample Sizes and Panel Attrition in the German Socio-Economic Panel (SOEP) (1984 until 2020). *SOEP Survey Papers*, *1106*.

Tucker, J., & Patrick, K. (2017). Low-wage jobs are women's jobs: the overrepresentation of women in low-wage work. *National Women's Law Center*.

Vuri, D. (2016). Do childcare policies increase maternal employment? *IZA World of Labor*, *241*.

Appendix A

Table A.1.i Descriptives of Covariates between Control and Treatment Groups

	Never-treated Control Group			Treatment Group					Difference in Group Proportions	
Variable	Obe	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Min	Max	z-value	p-value
Marital status										
Married	15957	0.55	0.497	97625	0.614	0.487	0	1	-15.1231	0
Single	15957	0.296	0.456	97625	0.25	0.433	0	1	11.8964	1
Widowed	15957	0.024	0.152	97625	0.012	0.108	0	1	9.5850	1
Divorced	15957	0.099	0.299	97625	0.094	0.292	0	1	1.9648	0.9753
Separated	15957	0.032	0.175	97625	0.03	0.169	0	1	1.3448	0.9107
Partner										
No partner	16029	0.338	0.473	98202	0.262	0.44	0	1	19.0422	1
Spouse	16029	0.549	0.498	98202	0.611	0.488	0	1	-14.6554	0
Partner	16029	0.109	0.311	98202	0.123	0.329	0	1	-5.2407	0.0001
Probably spouse	16029	0.002	0.042	98202	0.002	0.049	0	1	0	0.5
Probably partner	16029	0.002	0.047	98202	0.002	0.043	0	1	0	0.5
Unknown	16029	0	0.014	98202	0	0.01	0	1	0	0.5
High School (HS) Degree										
Less than HS	15483	0.214	0.41	95756	0.111	0.314	0	1	29.8749	1
HS Degree	15483	0.631	0.483	95756	0.566	0.496	0	1	15.4777	1
More than HS	15483	0.155	0.361	95756	0.323	0.468	0	1	-51.3486	0
Migrational background										
None	16029	0.648	0.478	98202	0.705	0.456	0	1	-14.0872	0
Direct	16029	0.285	0.452	98202	0.228	0.42	0	1	14.9473	1
Indirect	16029	0.067	0.25	98202	0.067	0.249	0	1	0	0.5

Note: The column 'Difference in Group Proportions' shows the z-statistic and p-value of a two-sample difference in proportions z-test under the Null hypothesis that the group proportions are the same.

Table A.1.ii Descriptives of Covariates between Control and Treatment Groups

	Never-treated Control Group			**Treatment Group**					**Difference in Group Means**	
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Min	Max	t-statistic	p-value
Years of Education	15189	11.485	2.334	94375	12.721	2.842	7	18	-50.9358	0
Age	160297	42.123	2.68	98202	43.379	11.369	18	67	-12.7526	0
Number of kids	15984	0.844	1.119	97952	0.898	1.116	0	11	-5.6755	0

Note: The column 'Difference in Group Means' shows the t-statistic and p-value of a two-sample difference in means t-test under the Null hypothesis that the group means are the same.

Table A.2 Event study estimation results on log hourly wages

	Males		Females	
	(1) Event	(2) Event incl. control	(3) Event	(4) Event incl. control
Pre Average	-0.0957*	-0.0565	-0.0620***	-0.0443*
	(-2.53)	(-0.95)	(-3.63)	(-2.53)
Post Average	0.594***	0.561***	0.404***	0.414***
	(22.59)	(21.01)	(26.65)	(25.49)
Tm5	-0.165	0.319	0.00101	-0.00395
	(-1.01)	(1.46)	(0.02)	(-0.07)
Tm4	-0.0184	-0.00665	-0.00758	-0.00105
	(-0.15)	(-0.06)	(0.14)	(-0.02)
Tm3	-0.0107	-0.0194	0.0224	0.0430
	(-017)	(-0.33)	(0.66)	(1.18)
Tm2	-0.0300	-0.0147	-0.144***	-0.155***
	(-0.49)	(-0.23)	(-4.32)	(-4.43)
Tm1	-0.374***	-0.384***	-0.342***	-0.323***
	(-11.48)	(-12.79)	(-17.42)	(-16.04)
Tp0	0.402***	0.402***	0.320***	0.316***
	(16.17)	(14.49)	(18.72)	(18.00)
Tp1	0.531***	0.507***	0.349***	0.339***
	(16.81)	(15.69)	(19.52)	(16.79)
Tp2	0.560***	0.545***	0.412***	0.433***
	(15.24)	(14.55)	(18.31)	(18.57)
Tp3	0.626***	0.597***	0.445***	0.453***
	(14.49)	(16.13)	(19.67)	(19.71)
Tp4	0.673***	0.636***	0.393***	0.435***
	(11.38)	(11.52)	(14.20)	(16.61)
Tp5	0.773***	0.681***	0.505***	0.508***
	(14.76)	(11.68)	(16.75)	(16.79)
N				

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.3 Estimation results on male log hourly wages

	Estimations without controls			Estimations with controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Simple	Calendar	Group	Simple	Calendar	Group
ATT	0.533***			0.512***		
	(23.75)			(22.15)		
Average		0.507***	0.509***		0.491***	0.490***
		(19.91)	(22.79)		(18.88)	(20.03)
2015		0.331***	0.547***		0.333***	0.520***
		(10.38)	(16.43)		(7.64)	(14.55)
2016		0.462***			0.453***	
		(10.38)			(10.04)	
2017		0.503***	0.556***		0.497***	0.538***
		(14.44)	(12.27)		(13.86)	(10.64)
2018		0.583***			0.559***	
		(13.97)			(13.41)	
2019		0.544***	0.494***		0.537***	0.488***
		(15.79)	(10.43)		(14.98)	(8.71)
2020		0.618***	0.433***		0.568***	0.399***
		(21.45)	(7.22)		(16.76)	(6.73)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.4 Estimation results on female log hourly wages

	Estimations without controls			Estimations with controls		
	(1)	(2)	(3)	(1)	(2)	(3)
	Simple	Calendar	Group	Simple	Calendar	Group
ATT	0.383***			0.389***		
	(27.78)			(28.48)		
Average		0.468***	0.395***		0.373***	0.394***
		(26.81)	(27.32)		(24.66)	(26.10)
2015		0.262***	0.364***		0.250***	0.372***
		(10.73)	(21.55)		(10.14)	(19.78)
2016		0.315***			0.305***	
		(13.42)			(17.89)	
2017		0.372***	0.446***		0.393***	0.461***
		(18.31)	(14.08)		(17.89)	(14.40)
2018		0.382***			0.393***	
		(18.06)			(16.92)	
2019		0.382***	0.326***		0.412***	0.320***
		(19.06)	(9.69)		(20.55)	(9.44)
2020		0.496***	0.512***		0.485***	0.469***
		(21.74)	(9.12)		(22.98)	(8.09)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.5 Event study estimation results on economic mobility

	Males		Females	
	(1)	(2)	(3)	(4)
	Event	Event incl. control	Event	Event incl. control
Pre Average	-0.133*	-0.265	-0.0610**	-0.0592**
	(-2.47)	(-1.90)	(-2.80)	(-2.77)
Post Average	0.355*	0.349***	0.235***	0.225***
	(10.54)	(9.58)	(13.69)	(11.73)
Tm5	-0.193	-0.819	-0.105	-0.0573
	(-0.74)	(-1.15)	(-0.90)	(-0.54)
Tm4	-0.181	-0.171	0.0721	0.0607
	(-1.25)	(-1.13)	(1.13)	(1.04)
Tm3	-0.0113	-0.0187	-0.0708	-0.0911
	(-0.06)	(-0.09)	(-1.19)	(-1.43)
Tm2	-0.0104	-0.0616	-0.0463	-0.0396
	(-0.11)	(-0.61)	(-1.17)	(-0.96)
Tm1	-0.270**	-0.253**	-0.155***	-0.169***
	(-3.16)	(1.63)	(-4.12)	(-4.48)
Tp0	0.721***	0.746***	0.397***	0.388***
	(17.79)	(16.31)	(18.01)	(18.31)
Tp1	0.354***	0.351***	0.244***	0.221***
	(8.09)	(7.48)	(10.94)	(9.95)
Tp2	0.270***	0.254***	0.208***	0.205***
	(4.76)	(4.52)	(7.91)	(7.07)
Tp3	0.306***	0.298***	0.188***	0.173***
	(5.63)	(5.49)	(7.28)	(6.03)
Tp4	0.306***	0.251***	0.212***	0.202***
	(4.03)	(-0.69)	(6.50)	(5.67)
Tp5	0.211**	0.193**	0.160***	0.163***
	(2.94)	(2.66)	(4.22)	(3.75)
N				

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.6 Estimation results on male economic mobility

	Estimations without controls			Estimations with controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Simple	Calendar	Group	Simple	Calendar	Group
ATT	0.449***			0.449***		
	(13.60)			(12.84)		
Average		0.424***	0.597***		0.419***	0.613***
		(12.98)	(14.62)		(12.37)	(13.68)
2015		0.388***	0.273***		0.0379***	0.250***
		(8.07)	(7.41)		(7.24)	(6.25)
2016		0.251***			0.216***	
		(4.33)			(3.50)	
2017		0.522***	0.575***		0.527***	0.599***
		(8.23)	(6.40)		(7.87)	(7.09)
2018		0.376***			0.353***	
		(6.41)			(5.94)	
2019		0.511***	0.606***		0.519***	0.645***
		(10.78)	(8.62)		(10.24)	(8.62)
2020		0.495***	1.104***		0.519***	1.174***
		(9.26)	(7.46)		(8.92)	(6.85)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.7 Estimation results on female economic mobility

	Estimations without controls			Estimations with controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Simple	Calendar	Group	Simple	Calendar	Group
ATT	0.266***			0.254***		
	(15.88)			(13.74)		
Average		0.260***	0.328***		0.248***	0.313***
		(15.09)	(15.95)		(14.88)	(15.15)
2015		0.293***	0.205***		0.286***	0.195***
		(11.40)	(9.93)		(10.30)	(8.32)
2016		0.201***			0.181***	
		(7.03)			(6.29)	
2017		0.289***	0.331***		0.275***	0.320***
		(10.72)	(8.55)		(10.10)	(8.08)
2018		0.281***			0.169***	
		(6.80)			(6.23)	
2019		0.307***	0.416***		0.301***	0.411***
		(12.30)	(8.93)		(11.10)	(8.57)
2020		0.289***	0.594***		0.277***	0.553***
		(10.75)	(7.30)		(9.46)	(6.49)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.8 Event study estimation results on working hours

	Males		Females	
	(1) Event	(2) Event incl. control	(3) Event	(4) Event incl. control
Pre Average	0.120	0.744	-0.574	-0.653
	(0.17)	(0.97)	(-1.54)	(-0.27)
Post Average	2.343***	1.921**	1.105**	0.990
	(3.54)	(2.80)	(2.90)	(0.97)
Tm5	1.207	3.674	-1.325	-10.58
	(0.48)	(1.19)	(-0.97)	(-0.87)
Tm4	0.613	1.088	-1.702	0.943
	(0.26)	(0.56)	(-1.24)	(0.36)
Tm3	-1.700	-1.797	-0.773	-0.0899
	(-1.13)	(-1.27)	(-0.91)	(-0.03)
Tm2	-0.955	-0.293	0.745	5.474**
	(-0.71)	(-0.20)	(0.91)	(3.14)
Tm1	0.404	0.797	1.448**	0.991
	(0.50)	(0.96)	(3.21)	(0.64)
Tp0	0.225	-0.124	-0.500	2.817*
	(0.38)	(-0.20)	(-1.30)	(2.04)
Tp1	2.607***	2.033**	0.636	-0.332
	(3.82)	(2.68)	(1.44)	(-0.24)
Tp2	2.573**	2.239**	0.876	3.438*
	(2.89)	(2.60)	(1.51)	(2.05)
Tp3	2.518**	2.247*	1.925***	1.872
	(2.60)	(2.37)	(3.56)	(1.21)
Tp4	3.090*	3.033*	1.960***	-1.999
	(2.40)	(2.19)	(2.65)	(-1.03)
Tp5	3.044*	2.100	1.734*	0.771
	(2.50)	(1.54)	(2.53)	(0.36)
N				

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.9 Estimation results on male working hours

	Estimations without controls			Estimations with controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Simple	Calendar	Group	Simple	Calendar	Group
ATT	1.850***			1.448***		
	(3.25)			(2.48)		
Average		1.712**	1.509**		1.387*	0.983
		(2.54)	(2.93)		(2.22)	(1.67)
2015		-0.539	2.065**		-0.592	1.780
		(-0.48)	(2.08)		(-0.53)	(1.95)
2016		1.874			1.708	
		(1.53)			(1.40)	
2017		1.965*	1.954		1.807*	1.671
		(2.24)	(1.88)		(2.09)	(1.70)
2018		3.039***			1.627**	
		(3.45)			(2.86)	
2019		1.848*	1.733		1.445	0.870
		(2.44)	(1.64)		(1.95)	(0.81)
2020		2.086**	-0.0133		1.325	-0.738
		(3.01)	(-0.01)		(1.94)	(-0.51)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.10 Estimation results on female working hours

	Estimations without controls			Estimations with controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Simple	Calendar	Group	Simple	Calendar	Group
ATT	0.765*			1.294		
	(2.13)			(1.42)		
Average		0.685	0.378		1.238	1.428
		(1.92)	(1.06)		(1.29)	(1.44)
2015		-0.616	0.955*		1.508	0.640
		(-1.03)	(2.00)		(1.58)	(0.54)
2016		0.609			-0.718	
		(0.97)			(-0.44)	
2017		0.439	0.932		1.167	3.255
		(0.87)	(1.36)		(0.83)	(1.83)
2018		1.565**			1.889	
		(2.89)			(1.27)	
2019		1.213*	0.201		1.937	-0.796
		(2.40)	(0.25)		(1.17)	(-0.26)
2020		0.902	-1.894		0.645	3.072
		(1.86)	(-1.50)		(0.43)	(0.92)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.11 Event study estimation results on part-time employment

	Males		Females	
	(1) Event	(2) Event incl. control	(3) Event	(4) Event incl. control
Pre Average	0.0104	-0.00615	0.0218	0.0270
	(0.50)	(-0.29)	(1.57)	(1.76)
Post Average	-0.121***	-0.117***	-0.0499**	-0.0626**
	(-5.79)	(-5.63)	(-3.47)	(-4.12)
Tm5	-0.0170	-0.0702	0.0299	0.0249
	(-0.24)	(-0.83)	(0.55)	(0.47)
Tm4	0.0157	-0.0155	0.0649	0.0487
	(0.24)	(-0.25)	(1.34)	(0.98)
Tm3	0.0484	0.0711	0.000235	-0.00206
	(1.11)	(1.61)	(0.01)	(-0.07)
Tm2	0.0336	0.0250	-0.0118	-0.00489
	(0.88)	(0.60)	(-0.39)	(-0.18)
Tm1	0.0301	0.0212	-0.0218	-0.0178
	(1.18)	(0.86)	(-1.33)	(-1.07)
Tp0	-0.0501*	-0.0401*	-0.0135	-0.0151
	(-2.51)	(-2.02)	(-0.92)	(-1.01)
Tp1	-0.106***	-0.0915***	-0.0345*	-0.0351*
	(-4.44)	(-3.64)	(-2.06)	(-2.04)
Tp2	-0.113***	-0.114***	-0.0548*	-0.0614**
	(-3.75)	(-3.65)	(-2.44)	(-2.93)
Tp3	-0.126***	-0.135***	-0.0713**	-0.0875***
	(-3.74)	(-4.39)	(-3.21)	(-3.97)
Tp4	-0.157***	-0.156***	-0.0640*	-0.0887**
	(-3.50)	(-3.66)	(-2.32)	(-3.00)
Tp5	-0.175***	-0.168***	-0.0613*	-0.0877**
	(-4.18)	(-3.86)	(-2.19)	(-2.86)
N				

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.12 Estimation results on male part-time employment

	Estimations without controls			Estimations with controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Simple	Calendar	Group	Simple	Calendar	Group
ATT	-0.0940***-			-0.0940***		
	(-5.24)			(-5.27)		
Average		-0.0922***	-0.883***		-0.0880***	-0.0767***
		(-4.82)	(-5.16)		(-4.16)	(-4.46)
2015		-0.0339	-0.111***		-0.0309	-0.109***
		(-0.98)	(-3.99)		(-0.85)	(-3.74)
2016		-0.0787*			-0.0695	
		(-2.18)			(-1.76)	
2017		-0.0874***	-0.0916**		-0.0917**	-0.0978**
		(-3.33)	(-2.76)		(-3.02)	(-2.73)
2018		-0.127***			-0.132***	
		(-4.76)			(-4.33)	
2019		-0.110***	-0.0997**		-0.0999***	-0.0712*
		(-4.76)	(-2.94)		(-3.88)	(-2.02)
2020		-0.117***	-0.0385		-0.103***	0.0169
		(-5.30)	(-0.90)		(-4.64)	(-0.36)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.13 Estimation results on female part-time employment

	Estimations without controls			Estimations with controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Simple	Calendar	Group	Simple	Calendar	Group
ATT	-0.0423**			-0.0513**		
	(-3.25)			(-3.60)		
Average		-0.0388**	-0.0354**		-0.0468**	-0.0421**
		(-2.81)	(-2.77)		(-3.11)	(-3.07)
2015		-0.00156	-0.0411*		0.00110	-0.0532**
		(0.07)	(-2.37)		(0.05)	(-2.81)
2016		-0.0136			-0.0568*	
		(0.57)			(-2.51)	
2017		-0.0489*	-0.0592*		-0.0907***	-0.0661*
		(-2.41)	(-2.28)		(-3.86)	(-2.49)
2018		-0.0736***			-0.0650***	
		(-3.39)			(-3.31)	
2019		-0.0532**	-0.0348		-0.0650***	-0.0309
		(-2.87)	(-1.20)		(-3.31)	(-1.05)
2020		-0.0448*	0.0163		-0.0571**	0.0107
		(-2.35)	(0.35)		(-2.82)	(0.24)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP v37, own calculations.

Table A.14 Event study estimation results on childcare outsourcing

	Males		Females	
	(1) Event	(2) Event with controls	(3) Event	(4) Event with controls
Pre Average	-4.954**	-8.265***	0.108	-0.653
	(-3.24)	(-4.30)	(0.08)	(-0.27)
Post Average	1.609	0.169	0.798	0.990
	(0.96)	(0.09)	(0.84)	(0.97)
Tm5	-19.33***	-33.27***	-7.619	-10.58
	(-14.43)	(-8.01)	(-1.20)	(-0.87)
Tm4	0.239	-0.428	5.097	0.943
	(0.44)	(-0.43)	(1.93)	(0.36)
Tm3	-2.996	-2.984	-0.401	-0.0899
	(-0.89)	(-0.85)	(-0.14)	(-0.03)
Tm2	-0.723	-2.027	3.229	5.474**
	(-0.29)	(-0.69)	(1.95)	(3.14)
Tm1	-1.960	-2.616	0.235	0.991
	(-0.97)	(-1.75)	(0.16)	(0.64)
Tp0	0.478	0.479	1.910	2.187*
	(0.54)	(0.52)	(1.78)	(2.04)
Tp1	-1.960	-0.0295	-0.583	-0.332
	(-0.97)	(-0.03)	(-0.49)	(-0.24)
Tp2	-0.0335	-1.658	0.218	3.438*
	(-0.02)	(-0.74)	(0.15)	(2.05)
Tp3	3.782	2.873	1.496	1.872
	(1.02)	(0.36)	(0.93)	(1.21)
Tp4	3.354	-1.698	0.989	-1.999
	(0.51)	(-0.22)	(0.46)	(-1.03)
Tp5	2.487	1.047	0.759	0.771
	(0.73)	(0.35)	(0.36)	(0.36)
N				

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.15 Estimation results on male childcare outsourcing

	Estimations without controls			Estimations with controls		
	(1) Simple	(2) Calendar	(3) Group	(4) Simple	(5) Calendar	(6) Group
ATT	0.821			0.231		
	(0.63)			(0.17)		
Average		0.913	0.307		1.000	0.136
		(0.62)	(0.40)		(0.69)	(0.18)
2015		2.223	2.508		0.199	2.632
		(0.86)	(1.10)		(0.06)	(1.05)
2016		1.360			-0.362	
		(0.66)			(-0.17)	
2017		0.677	-1.797		0.762	-4.829^{*}
		(0.31)	(-0.50)		(0.43)	(-2.04)
2018		-0.289			9.252^{*}	
		(-0.12)			(1.96)	
2019		0.612	0.970		-1.515	0.229
		(0.35)	(1.35)		(-0.62)	(0.20)
2020		0.894	-0.570		-2.337	0.825
		(0.80)	(-0.77)		(-1.25)	(0.98)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table A.16 Estimation results on female childcare outsourcing

	Estimations without controls			Estimations with controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Simple	Calendar	Group	Simple	Calendar	Group
ATT	0.847			1.294		
	(0.98)			(1.42)		
Average		0.879	0.546		1.238	1.428
		(0.92)	(0.65)		(1.29)	(1.44)
2015		3.000	1.249		2.508	0.640
		(1.89)	(1.03)		(1.58)	(0.54)
2016		-0.617			-0.718	
		(-0.38)			(-0.44)	
2017		0.784	0.355		1.167	3.255
		(0.58)	(0.21)		(0.83)	(1.83)
2018		1.579			1.889	
		(1.08)			(1.27)	
2019		0.810	0.00347		1.937	-0.796
		(0.52)	(0.00)		(1.17)	(-0.26)
2020		-0.282	-0.657		0.645	3.072
		(-0.21)	(-0.23)		(0.43)	(0.92)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Appendix B

Table B.1

Robustness Test on log hourly wages using only contractual working hours

	Males			Females		
	(1) Simple	(2) Calendar	(3) Group	(4) Simple	(5) Calendar	(6) Group
Controls	yes	yes	yes	yes	yes	yes
ATT	0.389***			0.354***		
	(38.41)			(29.56)		
Average		0.371***	0.378***		0.338***	0.355***
		(34.33)	(34.61)		(28.06)	(28.36)
2015		0.245***	0.379***		0230***	0.332***
		(13.24)	(25.39)		(10.41)	(19.79)
2016		0.319***			-0.273***	
		(17.41)			(12.84)	
2017		0.380***	0.439***		0.349***	0.426***
		(23.13)	(21.91)		(17.14)	(16.54)
2018		0.402***			0.352***	
		(24.14)			(16.16)	
2019		0.429***	0.369***		0.392***	0.331***
		(27.50)	(15.10)		(22.44)	(11.11)
2020		0.452***	0.307***		0.434***	0.343***
		(29.12)	(7.70)		(22.36)	(6.64)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table B.2

Robustness Test: Event study estimation results on log hourly wages using only contractual working hours

	Males	**Females**
	(1)	(2)
	Event with controls	Event with controls
Pre Average	-0.0361**	-0.0335*
	(-2.63)	(-2.15)
Post Average	0.419***	0.375***
	(37.37)	(27.43)
Tm5	0.0223	0.0459
	(0.45)	(0.94)
Tm4	-0.0158	-0.0480
	(-0.33)	(-0.97)
Tm3	0.0510	0.0626
	(1.88)	(1.94)
Tm2	0.0986***	-0.116***
	(-4.06)	(-4.41)
Tm1	-0.285***	-0.292***
	(-18.18)	(-16.65)
Tp0	0.301***	0.288***
	(26.10)	(-16.65)
Tp1	0.366***	0.319***
	(26.45)	(19.82)
Tp2	0.427***	0.288***
	(25.21)	(-16.65)
Tp3	0.449***	0.405***
	(29.23)	(19.53)
Tp4	0.468***	0.399***
	(21.88)	(15.33)
Tp5	0.505***	0.451***
	(21.32)	(15.89)
N		

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP v37, own calculations.

Table B.3

Robustness Test on weekly working hours using only contractual working hours

	Males			Females		
	(1)	(2)	(3)	(4)	(5)	(6)
	Simple	Calendar	Group	Simple	Calendar	Group
Controls	yes	yes	yes	yes	yes	yes
ATT	2.087***			1.738***		
	(3.51)			(4.77)		
Average		2.019**	1.513**		1.667***	1.173***
		(3.21)	(2.79)		(4.37)	(3.32)
2015		0.635	2.344**		0.549	2.143***
		(0.57)	(2.60)		(0.85)	(4.71)
2016		1.846			1.287***	
		(1.60)			(1.80)	
2017		2.419**	2.502*		1.389*	1.819*
		(3.08)	(2.35)		(2.42)	(2.53)
2018		3.172***			3.007***	
		(3.70)			(5.04)	
2019		2.351**	1.939		2.070***	0.122
		(2.97)	(1.88)		(3.99)	(0.14)
2020		1.688*	-0.999		1.697***	-1.267
		(2.35)	(-0.71)		(3.37)	(-1.03)
N						

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP, own calculations.

Table B.4

Robustness Test: Event study estimation results on working hours using only contractual working hours

	Males	**Females**
	(1) Event with controls	(2) Event with controls
Pre Average	0.273	-0.439
	(0.46)	(-1.22)
Post Average	2.483***	2.174***
	(3.68)	(5.58)
Tm5	-3.809	-0.949
	(-1.29)	(-0.67)
Tm4	0.355	-0.616
	(0.16)	(-0.48)
Tm3	-2.572	-0.383
	(-1.79)	(-0.44)
Tm2	1.669	0.479
	(1.17)	(0.60)
Tm1	0.751	0.694
	(0.88)	(1.47)
Tp0	0.828	0.295
	(1.28)	(0.72)
Tp1	2.348***	1.295***
	(3.41)	(2.74)
Tp2	2.810**	1.884***
	(3.16)	(3.13)
Tp3	3.271***	3.076***
	(29.23)	(5.19)
Tp4	3.320*	3.257***
	(2.39)	(4.32)
Tp5	2.318	3.235***
	(1.82)	(4.37)
N		

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEP v37, own calculations.