Essays in Empirical Labour Economics

Von der Fakultät Staatswissenschaften
der Leuphana Universität Lüneburg

zur Erlangung des Grades
Doktor der Wirtschafts- und Sozialwissenschaften
Dr. rer. pol.

genehmigte Dissertation von
Philipp Lentge

aus
Dessau

Eingereicht am: 06.12.2022

Mündliche Verteidigung (Disputation) am: 11.04.2023

Erstbetreuer und -gutachter:	Prof. Dr. Boris Hirsch
Zweitgutachter:	Prof. Dr. Thomas Zwick
Drittgutachter:	Prof. Dr. Mario Mechtel

Die einzelnen Beiträge des kumulativen Dissertationsvorhabens sind wie folgt veröffentlicht:

ARTIKEL IN REFERIERTEN ZEITSCHRIFTEN

„Non-base compensation and the gender pay gap“, *LABOUR: Review of Labour Economics and Industrial Relations*, 36(3) (2022): 277-301 (mit B. Hirsch)

„Uncovered workers in plants covered by collective bargaining: Who are they and how do they fare?“, *British Journal of Industrial Relations*, 60(4) (2022): 929-945 (mit B. Hirsch und C. Schnabel)

WORKING PAPER

„Second job holding in Germany - a persistent feature?“, Working Paper Series in Economics No. 416, Lüneburg, 2022

Veröffentlichungsjahr: 2023

Veröffentlicht im Onlineangebot der Universitätsbibliothek unter der URL:
`http://www.leuphana.de/ub`

To my parents

Acknowledgements

First of all and with the greatest gratitude, I would like to thank my academic supervisor Boris Hirsch for his valuable guidance and perpetual support in pursuing this dissertation. An open door but more importantly an open ear for all kinds of questions created a wholesome and stimulating work atmosphere.

Second, I would like to thank the whole Institute of Economics for upholding a way of working together that goes beyond just a regular work day. Determined and pragmatic work, joint lunches, after work drinks or barbecues made the time at the institute memorable. I would like to thank Mario Mechtel, Christian Pfeifer, Thomas Wein, Christoph Wegener, Luise Görges, Michael Lamla, Joachim Wagner and Thomas Huth, Professors at the Institute of Economics, for fruitful discussions in our seminar and for sustaining an atmosphere enjoyable to work in.

A very special thank you goes to the institute's secretaries Christina Korf, Maike Mente and Sabine Brodt, for their relentless effort in all organizational matters — large or small. Many thanks go to my colleagues Arne, Katja, Inna, Mats, Miguel, Tam and Stefano, who always had an open door to chat research or else.

I also thank my co-author Claus Schnabel for the cooperation on one of this thesis' papers. I benefited a lot during this cooperation from his experience and work ethic.

Last but not least, on a personal level, I am grateful to my parents and my brother for their support and motivation, as well as to Malena for her patience and ongoing encouragement during this endeavour.

Lüneburg, November 2022

Inhaltsverzeichnis

1 Introduction

Facts do not cease to exist because they are ignored.

Aldous Huxley

Labour markets are crucial components of any economy and the focus of many researchers, as labor markets are the field of many policy interventions along with their intended and unintended consequences. This dissertation comprises three stand-alone research papers dealing with different aspects of labor market characteristics, labor market inequality, and gender differentials: bonus payments and the gender pay gap, second job holding, and workers uncovered by collective bargaining. The common factor of these papers is the empirical approach and making use of the actual data to accurately describe the situations in the labor market, as well as to quantify the relationships between various characteristics of workers and their labor market outcomes.

The first paper "Non-base compensation and the gender pay gap" (with B. Hirsch) investigates whether non-base compensation in the form of bonus payments, overtime pay, and shift premia contributes to the gender pay gap. Using administrative linked employer-employee data (Structure of Earnings Survey) from Germany, we investigate how these non-base compensation components contribute to the gender pay gap both at the mean and at different quantiles of the wage distribution. Firstly, we find at the descriptive level, that bonus payments are less prevalent and also less sizeable among women than men, resulting in a substantially higher gender pay gap if bonuses are included in the analysis. We further document that the same holds for shift premia and overtime pay, but that these are far less prevalent among workers than bonuses, rendering their scope for contributing to the gender pay gap limited.

But one might ask, whether gender differences in bonus payments merely reflect that women are underrepresented in higher hierarchy levels where bonus payments are disproportionately important. Our data allow us to distinguish hierarchy levels for workers

in our sample. Therefore we can show that women are underrepresented among the higher echelons and that marked gender differences in bonus payments persist within hierarchy levels.

In our econometric analysis we perform Oaxaca-Blinder decompositions at the mean and at various quantiles of the unconditional wage distribution based on recentered influence functions. In doing so, we find that bonus payments's absolute contribution to the gender pay gap is rising as we move up the wage distribution and that their relative contribution is more or less constant around 10 percent. Among higher echelon workers, we find that gender differences in bonuses become the most important contributor to the gender pay gap when moving up the wage distribution, lending more evidence to glass ceilings in bonuses that translate into glass ceilings in total pay. This might be in line with the notion that employers use their larger discretion over bonus payments compared with base salaries to discriminate against women as well as with the notion of men negotiating harder than women over bonuses.

Overall, our findings suggest that gender differences in bonuses are an important contributor to the gender pay gap, particularly in top jobs.

Unionization along with collective bargaining coverage has been on the decline in recent decades. Using German administrative data, the second paper (with B. Hirsch and C. Schnabel) examines which workers in firms covered by collective bargaining agreements still individually benefit from these union agreements, which workers are not covered anymore and what this means for their wages.

We document how large the share of workers in plants covered by collective bargaining who do not enjoy effective individual coverage anymore is and who the workers who are not individually covered are. Additionally, we investigate the wage implications of workers not being individually covered and ask wether unions still achieve their goal of protecting the most disadvantaged workers, such as low-skilled and low-paid workers. Our descriptive findings show that about 9 percent of workers in plants with collective agreements do not enjoy individual coverage anymore. We further find that individual non-coverage is more

prevalent among men, managers and workers in the bottom and the top quarter of the wage distribution.

The results of our econometric analyses with unconditional quantile regressions and firm-fixed-effects estimations demonstrate that not being individually covered by a collective agreement has serious wage implications for most workers. Low-wage non-union workers and those at low hierarchy levels particularly suffer since employers abstain from extending union wages to them, in such a way jeopardizing unions' goal of protecting all disadvantaged workers.

In the third paper, I study the development and persistence of second job holding in Germany after a legislative change in the year 2003 allowed the extensive dispensation of marginal second jobs from taxes and social security contributions. Using data from the German Socio-Economic Panel I document a substantial increase in second job holding in Germany since 2003 that is mainly driven by women engaging in more than one job. This trend is especially strong for marginal second jobs taken up by women, which increased by almost 200 percent up to the year 2019. My descriptive findings further document significant differences in marginal second job holding across different socio-economic worker groups, where especially low income and low skill workers hold a marginal second job.

What is more, there is strong descriptive evidence for a considerable persistence of second job holding. I find in panel estimations that low income, low tenure, part-time, and hours constrained women have a higher probability to take up a marginal second job. Moreover, I estimate a dynamic multinomial logit model with random effects and find that there is true state dependence in second job holding, especially for marginal second employment, meaning that once a worker is in, she is in. This state dependence is even more pronounced for women than for men.

In conclusion, my results show that gender differences in second job holding exist and that women in particular responded to the legislative change, which allowed for tax and social security contribution exempt second jobs.

In my opinion, these three papers each contribute to the literature in examining more closely labor market situations and trends that have been going on for quite some time, but have been insufficiently researched so far. Although the papers investigate different topics, one common outcome trend is visible: Often women are still at a disadvantage compared to their male counterparts and also workers in less than ideal situations (e.g. low skills, low income, part time) are often most at risk to suffer unfavorable labor market outcomes. Therefore it must remain a main policy goal to abolish these inequalities and to ensure support for vulnerable groups in labour markets.

DOI: 10.1111/labr.12229

ORIGINAL ARTICLE

Non-base compensation and the gender pay gap

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Abstract

This paper investigates whether non-base compensation contributes to the gender pay gap (GPG). Using administrative data from Germany, we find in wage decompositions that lower bonus payments to women explain about 10 per cent of the gap at the mean and at different quantiles of the unconditional wage distribution whereas the lower prevalence of shift premia and overtime pay among women is unimportant. Among managers, the contribution of bonuses to the mean gap more than doubles and is steadily rising as one moves up the wage distribution. Our findings suggest that gender differences in bonuses are an important contributor to the GPG, particularly in top jobs.

JEL CLASSIFICATION

J31, J71

1 | INTRODUCTION

Studies investigating the gender pay gap (GPG) are legion and continue to document substantial pay differences between men and women (recent surveys include Blau & Kahn, 2017 and Kunze, 2018). Although gender differences in employment rates and working hours have been continuously falling, marked pay differences persist. As equal pay and equal treatment of women figure prominently in public debates and high on many policymakers' agenda, this current state of affairs has left commentators and scientists alike asking 'Have women gone as far as they can?' (Blau & Kahn, 2007) and wondering what factors continue to contribute to the GPG.

This paper adds to this literature in investigating how non-base compensation in the form of bonus payments, overtime pay, and shift premia contributes to the GPG both at the mean

and at different quantiles of the wage distribution. At the descriptive level, we document that bonuses are less prevalent and also less sizeable among women than men. Although the same holds for shift premia and overtime pay, these are far less prevalent among workers than bonuses, rendering their scope for contributing to the GPG limited. In Oaxaca–Blinder (OB) wage decompositions at the mean and other unconditional quantiles, we find that lower bonuses received by women explain about 10 per cent of the GPG at the mean and beyond whereas overtime pay and shift premia are unimportant. Among managers, the contribution of bonuses to the mean GPG is 23 per cent and their contribution is also steadily rising along the wage distribution. Our reading of these results is that gender differences in bonuses are an important contributor to the GPG, particularly among the higher echelons.

Turning to the existing literature, recent contributions based on quantile regressions document that the GPG is more pronounced at the top of the wage distribution than at the bottom (e.g., Antonczyk et al., 2010; Arulampalam et al., 2007; Christofides et al., 2013; Collischon, 2019; Xiu & Gunderson, 2014), which is clearly in line with so-called glass ceilings. Moreover, Kassenboehmer and Sinning (2014) find that the narrowing of the GPG is mostly driven by falling wage differences at the bottom of the wage distribution or less so-called sticky floors. In contrast and women's educational catch-up in educational attainment notwithstanding, glass ceilings at the top did not change much. Furthermore, Goldin (2014) observes that gender pay differences attributable to productivity differences have almost vanished and that persisting differences largely stem from occupational differences. She further argues that flexibility and working hours arrangements, and thus arguably non-base compensation related to flexible working hours, are among the foremost contributors to the GPG, particularly among top earners.

That said, vertical segregation is still a widespread phenomenon with women being underrepresented in the higher echelons. It is well-documented that women are less likely to climb job ladders and receive promotions (e.g., Blau & Devaro, 2007; Kunze & Miller, 2017; Lazear & Rosen, 1990; Ransom & Oaxaca, 2005), and Fortin et al. (2017) further show that the underrepresentation of women in top jobs exacerbates the GPG at the top. But even within top jobs, women receive lower wages than men and a significant GPG remains (e.g., Bertrand & Hallock, 2001; Christofides et al., 2013; Pfeifer, 2014). In top jobs, in turn, base salaries play a lesser role and non-base compensation is both more widespread and more sizeable than in average jobs. Hence, persistent gender differences in non-base compensation may be behind the finding of largely intact glass ceilings.

This explanation would square up with the observation that women in top jobs receive lower bonuses (e.g., Grund, 2015; Kulich et al., 2011). What is more, base salaries are arguably to a much larger extent set by administrative rules and company regulations than non-base compensation. Hence, we suspect employers to possess more discretion over non-base compensation than base salaries, which is likely to lead to additional gender pay differences in top jobs because women negotiate less aggressively than men (e.g., Babcock & Laschever, 2003; Gneezy et al., 2003; Ors et al., 2013) and/or because of employers' additional scope for discrimination.

Evidence on the importance of non-base compensation on the GPG is rare. Usually, studies investigating the GPG analyse gross hourly wages and either omit non-base compensation entirely or do not disentangle base salaries and non-base compensation, for example, because survey data just ask for overall labor income and thus do not contain the relevant information for doing so. That said, the sparse existing evidence suggests that non-base compensation may be one important contributor to the GPG.

Investigating middle managers from the chemical industry in Germany, Grund (2015) finds that gender differences in bonus payments are more pronounced than gender differences in

base salaries and that bonus payments are more widespread and larger for higher echelons. Furthermore, Grund and Hofmann (2018) document that bonus–base salary ratios differ substantially across employers, pointing at employers' discretion in setting bonus payments. For the United States, McGee et al. (2015) find that women are less likely to work in jobs with performance pay and that different recipience of performance pay accounts for part of the GPG. Finally, Collischon (2019) documents a larger GPG at the top of the German wage distribution that widens further once bonus payments are included in workers' earnings. Yet, to the best of our knowledge no study has investigated in detail how non-base compensation affects the GPG, particularly among top earners.

Against this backdrop, we contribute to the existing literature along three dimensions. In contrast to most existing studies, our high-quality, representative linked employer–employee data for Germany includes detailed information on non-base compensation that we will use, first, to document gender differences in non-base compensation stemming from bonus payments, shift premia, and overtime pay. Our core finding will be that all these forms of non-base compensation are less prevalent and also less sizeable among women than among men.

We will, second, use this information to investigate in OB wage decompositions how non-base compensation contributes to the GPG both at the mean and beyond. The main result will be that a substantial part of the GPG is due to gender differences in bonus payments, both at the mean and along the wage distribution, whereas shift premia and overtime pay are unimportant.

Finally, our data also includes information on hierarchy levels, and we will use this information to examine the GPG among higher echelons. Our key result will be that bonus payments, which are particularly widespread and sizeable among workers holding top jobs, are particularly important for the GPG of managers and rise in importance as one moves up the wage distribution. We will further see that gender differences in bonus payments are by far the most important source of glass ceilings at the top of the top, that is of managers' GPG at the ninth decile of the wage distribution.

The remainder of this paper is organized as follows. Section 2 describes our data and provides descriptive findings on the prevalence and size of non-base compensation. Section 3 explains our estimation strategy based on wage decompositions, and Section 4 presents our decomposition results. Section 5 discusses our findings including possible *caveats*, and Section 6 concludes.

2 | DATA AND DESCRIPTIVE FINDINGS

Our data come from the Structure of Earnings Survey (*Verdienststrukturerhebung*) for the year 2014 (VSE 2014 henceforth), which is provided as a scientific use file by the Federal Statistical Agency (*Statistisches Bundesamt*) of Germany (for details, see Federal Statistical Agency, 2016). The VSE 2014 is a representative survey of all German firms with at least one worker and contains information on about 71,000 firms and 1 million workers. The data quality of these rich linked employer–employee data is high because most observations stem from firms' personnel records and firms are obliged by law to answer the survey correctly. The VSE 2014 thus differs from other survey data for Germany, such as the Socio-Economic Panel, in terms of sample size and its mandatory nature. It further differs from administrative data, in particular social security data provided by the Institute for Employment Research (*Institut für Arbeitsmarkt- und Berufsforschung*), in that it contains detailed information on working hours and the included

wage information is not subject to censoring, thereby allowing detailed analyses of top earners' hourly wages.[1]

The VSE 2014 data include detailed characteristics of both workers and firms. Worker characteristics comprise, inter alia, workers' earnings, base salaries, and non-base compensation components; their age, job tenure, and working hours; information on educational attainment, hierarchy levels, temporary (as opposed to permanent) contracts, and occupation.[2] Firm characteristics include information on firm size, workplace size, sector, and coverage by collective wage agreements. We use these data to build up a sample of workers aged 18–65 years employed in the private sector excluding apprentices, marginally employed, partial retirees, and temporary agency workers. Our final sample comprises 461,404 workers, with descriptive statistics given in Table 1.

In our analysis of the contribution of non-base compensation to the GPG, we exploit the rich information on remuneration components in the VSE data. Our outcome variable of interest are gross hourly wages comprising both base salaries and non-base compensation and are based on actual working hours (including overtime hours). Non-base compensation includes shift premia, overtime pay, and bonus payments, where the latter comprise all irregular, non-monthly payments such as incentive bonuses, profit sharing, stock options, vacation pay, Christmas bonuses, bonuses for improvement suggestions, and bonuses for inventions. Specifically, our wage variable adds up gross hourly wages including overtime pay and shift premia and bonus payments per hour worked.

As is visible from Table 1 that reports descriptives for our unweighted sample, there is a substantial raw average GPG in gross hourly wages excluding bonus payments of €4.95 or 24 per cent (relative to men's wages) that rises to about €5.87 or 26 per cent when wages include bonuses, which will be the outcome variable in our wage decompositions. Figure 1 displaying kernel density plots of log gross hourly wages including bonuses by gender (weighted using the VSE's sample weights as all following descriptives) suggests a more pronounced GPG in the upper part of the wage distribution as all quantiles of the male distribution are larger than the respective quantiles of the female distribution, and particularly so for the right tails. This impression is also borne out in Figure 2 that shows the GPG over the wage distribution, that is the percentage gap of every percentile in the male and the female wage distributions (e.g., the percentage gap between the median wage of men and women). No matter whether wages include or exclude bonuses, the GPG is monotonously increasing as one moves up the wage distribution, which is consistent with substantial glass ceilings.

Turning to workers' non-base compensation, we see from Table 1 that 71 per cent of workers in our sample receive some bonus payments and that women are not only less likely than men (68 per cent vs. 73 per cent) to receive any bonus payments but also obtain less sizeable bonus payments (€1972 vs. €4127 per year on average or €2882 vs. €5623 per year on average for recipients).[3] Figure 3 plotting the quantiles of bonus payments by gender further reveals that bonuses are substantially lower for women than for men over the entire distribution.

However, as women receive lower base salaries as well, we should expect some discrepancies in bonuses. In a next step, we thus normalize bonus payments by workers' full remuneration and consider the bonus-to-income ratio instead.[4] As is visible from Figure 4, bonus-to-income ratios are markedly lower for women than for men over the entire distribution as well, but less so than absolute bonus payments. Gender differences in bonuses may thus be a contributor to the GPG, particularly among top earners with large bonuses. This suggestion is borne out in Figure 2 showing that in the upper part of the wage distribution the GPG is larger when wages include bonus payments, and bonuses contribute more and more to the GPG when

TABLE 1 Descriptive statistics

	All		Men		Women	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Gross hourly wage (€)	19.75	14.11	22.43	16.49	16.56	9.69
Wage excl. bonus payments (€)	18.10	11.27	20.36	12.96	15.41	8.04
Bonus payments (0/1)	0.71	0.45	0.73	0.44	0.68	0.46
Bonus payments (€/year)	3143.75	8890.40	4127.6	11,053.56	1971.91	5012.79
Bonus-to-income ratio	0.06	0.07	0.07	0.07	0.05	0.06
Shift premium (0/1)	0.22	0.41	0.24	0.43	0.19	0.39
Shift premium (€/month)	43.04	148.45	59.07	184.43	23.94	84.25
Overtime pay (0/1)	0.09	0.29	0.13	0.33	0.06	0.24
Overtime pay (€/month)	31.20	151.31	45.4	186.81	14.29	89.86
Paid hours (monthly)	153.00	34.78	164.81	24.88	138.93	39.36
Paid overtime hours (monthly)	1.71	7.58	2.33	8.93	0.97	5.46
Age (years)	43.00	11.30	42.99	11.19	43.02	11.43
Tenure (years)	9.63	9.49	10.13	9.9	9.03	8.94
Skill level						
Low skilled (0/1)	0.11	0.31	0.1	0.3	0.12	0.33
Medium skilled (0/1)	0.69	0.46	0.66	0.47	0.71	0.45
High skilled (0/1)	0.20	0.40	0.23	0.42	0.17	0.37
Full-time employment (0/1)	0.72	0.45	0.9	0.3	0.51	0.5
Temporary contract (0/1)	0.13	0.34	0.12	0.32	0.15	0.36
Firm size						
<50 workers (0/1)	0.30	0.46	0.29	0.46	0.31	0.46
50–249 workers (0/1)	0.30	0.46	0.31	0.46	0.29	0.46
250 and more workers (0/1)	0.39	0.49	0.39	0.49	0.39	0.49
Workplace size	666.61	2669.96	811.36	3209.13	494.21	1816.17
East Germany (0/1)	0.19	0.39	0.18	0.38	0.19	0.39
Hierarchy level						
Manager (0/1)	0.08	0.27	0.11	0.31	0.05	0.22
Specialist (0/1)	0.17	0.38	0.2	0.4	0.14	0.35
Experienced worker (0/1)	0.51	0.50	0.49	0.5	0.54	0.5
No decision-making (0/1)	0.16	0.36	0.15	0.35	0.17	0.38
Simple tasks (0/1)	0.07	0.26	0.06	0.23	0.1	0.3
Collective agreement						
Sector-level agreement (0/1)	0.32	0.47	0.32	0.47	0.33	0.47
Firm-level agreement (0/1)	0.07	0.26	0.07	0.25	0.08	0.28
Observations	461,404		250,821		210,583	

Note: VSE 2014, unweighted data.

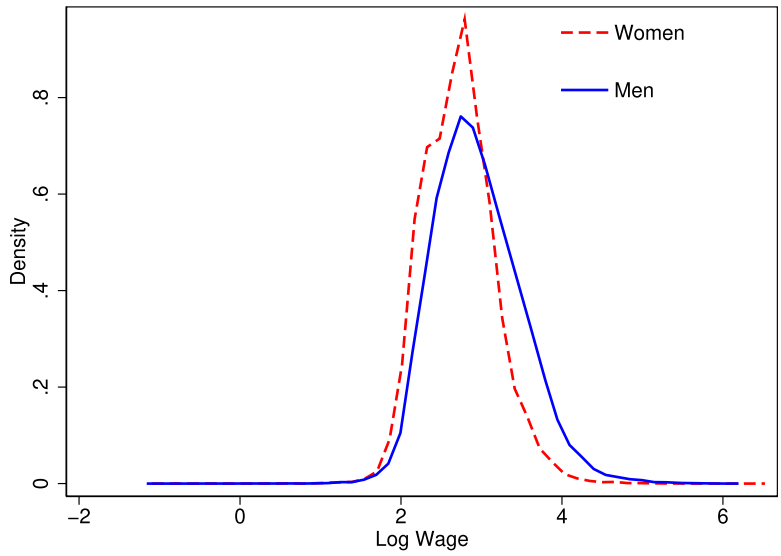

FIGURE 1 Kernel density plots of log gross hourly wages (including bonus payments) by gender (VSE 2014, weighted using sample weights)

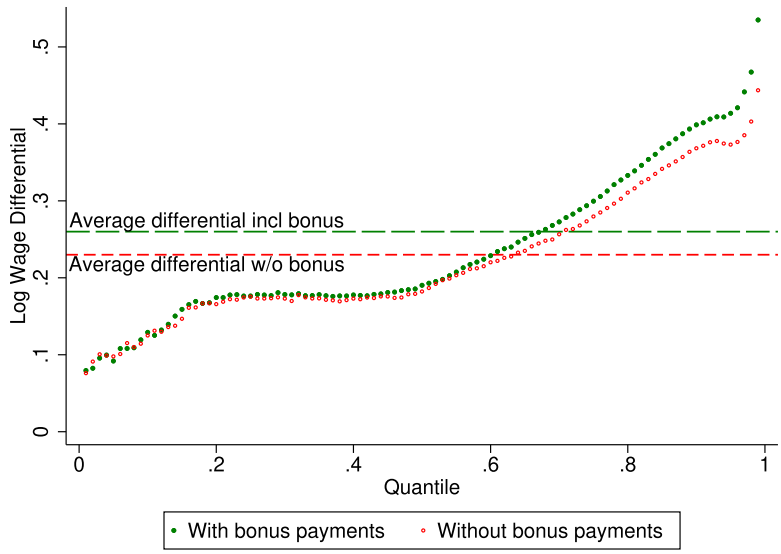

FIGURE 2 Gender pay gap in log gross hourly wages (including bonus payments) by quantile (VSE 2014, weighted using sample weights)

moving up the wage distribution (see also Table 3 that compares the GPG along the wage distribution when wages either exclude or include bonus payments).

But could not gender differences in bonus payments merely reflect that women are underrepresented in higher hierarchy levels where bonus payments are disproportionately important? In a next step, we thus focus on the distribution of bonus payments within hierarchy levels. The VSE 2014 distinguishes five different hierarchy levels (details are in Appendix A): workers with simple tasks, workers without decision-making, experienced workers, specialists, and workers with managerial duties (called managers henceforth). And indeed Table 2 shows that women are underrepresented among the higher echelons, that is specialists and managers, but overrepresented in the lower ranks, that is the three lower hierarchy levels.

That said, we observe that marked gender differences in bonus payments persist within hierarchy levels and that they are most pronounced among managers and specialists, that is in top

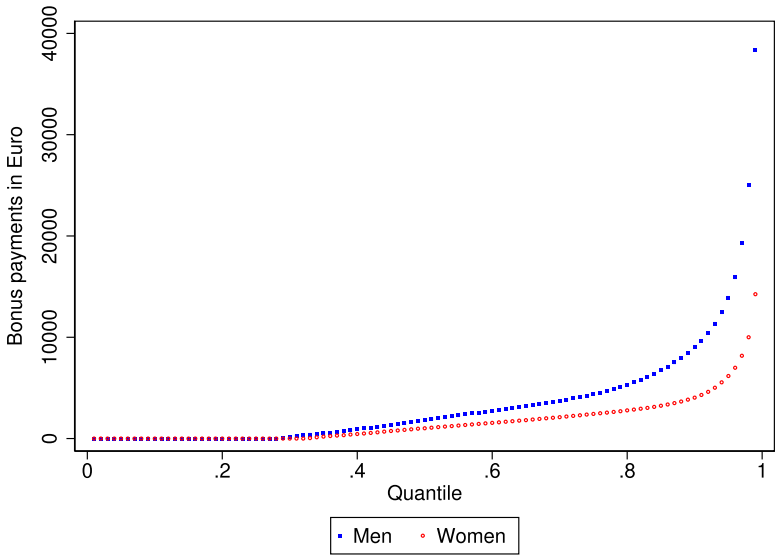

FIGURE 3 Quantiles of bonus payments by gender (VSE 2014, weighted using sample weights)

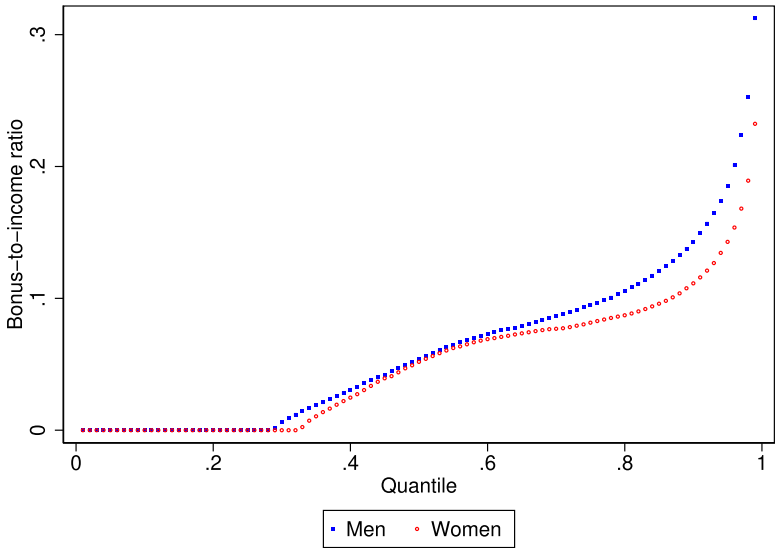

FIGURE 4 Quantiles of bonus-to-income ratios by gender (VSE 2014, weighted using sample weights)

jobs where bonus payments are widespread and make up a substantial part of most workers' overall remuneration. These findings strongly suggest that gender differences in bonus payments may be one important contributor to the GPG among top earners. This suggestion is further substantiated in Table 3 that shows that the GPG is not only larger in the upper part of the wage distribution, for higher hierarchy levels, and in the upper part of the wage distribution within hierarchy levels, but even more so when wages include bonus payments.[5] In short, gender differences in bonuses have the potential to be an important contributor to glass ceilings.[6]

Related to these findings, Goldin (2014) concludes that the GPG would to be low when wages are linear with respect to workings hours, but large when they are strictly convex. Our findings seem to indicate a similar convexity in the relationship between job positions and wages which is further strengthened when bonus payments are included. As, for instance, standard tournament theory predicts and empirical evidence documents, moving up the career ladder raises workers' wages and bonuses disproportionately (e.g., DeVaro, 2006; Eriksson, 1999; Lazear & Rosen, 1990; Lazear & Shaw, 2007). Given women's lower promotion probability, the

TABLE 2 Share of workers at different hierarchy levels

Hierarchy level	Men (%)	Women (%)	Total (%)
Manager	11.4	5.1	8.4
Specialist	19.5	13.8	16.7
Experienced worker	49.8	57.9	53.7
No decision-making	14.1	15.2	14.6
Simple tasks	5.3	8.1	6.6

Note: VSE 2014, weighted using sample weights.

TABLE 3 Gender pay gaps in gross hourly wages along the wage distribution

	Mean	p10	p25	p50	p75	p90
Excluding bonus payments						
Overall	23%	12%	16%	17%	24%	31%
Manager	23%	19%	22%	20%	22%	25%
Specialist	17%	12%	13%	17%	21%	19%
Experienced worker	12%	11%	10%	8%	12%	16%
No decision-making	14%	4%	8%	14%	15%	20%
Simple tasks	8%	−4%	1%	10%	10%	14%
Including bonus payments						
Overall	26%	12%	16%	17%	26%	33%
Manager	26%	19%	23%	23%	26%	29%
Specialist	19%	13%	15%	18%	22%	20%
Experienced worker	12%	12%	10%	8%	12%	17%
No decision-making	15%	4%	8%	14%	15%	22%
Simple tasks	7%	−4%	1%	9%	9%	13%

Note: VSE 2014, weighted using sample weights.

GPG is thus expected to rise as workers' careers progress and men disproportionately more often move into higher hierarchy levels and higher quantiles of the wage distribution, and particularly so when workers' remuneration includes bonus payments, which are more prevalent and sizeable in top jobs.

Turning to shift premia and overtime pay, we see from Table 1 that only a minority of workers in our sample receive these forms of non-base compensation and further that they are typically modest in size. Twenty-two per cent of workers obtain shift premia (24 per cent of men vs. 19 per cent of women) with an average premium of €43 per month for all workers (€59 for men vs. €24 for women) and €197 per month for recipients (€247 for men vs. €124 for women). Moreover, 9 per cent of workers get overtime pay (13 per cent of men vs. 6 per cent of women) with an average amount of €31 per month for all workers (€45 for men vs. €14 for women) and €329 per month for recipients (€363 for men vs. €243 for women). Hence, the scope of these forms of non-base remuneration to contribute significantly to the GPG appears to be limited.

In summary, our descriptive findings strongly suggest that gender differences in bonus payments are an important contributor to the GPG, particularly at the top of the wage distribution and at higher hierarchy levels, whereas other forms of non-base compensation are unlikely to play an important role. In a next step, we will run several wage decompositions to quantify the contribution of bonus payments and other forms of non-base compensation to the GPG along the wage distribution.

3 | ESTIMATION STRATEGY

Our econometric approach rests on several OB decompositions (Blinder, 1973; Oaxaca, 1973) that we perform at the mean and at several quantiles of the unconditional wage distribution, for example, for the gap between the median log wage of men and women, treating men as reference category. These OB decompositions of workers' log gross hourly wages including non-base compensation split up the overall GPG into an 'explained' part due to gender differences in covariates and an 'unexplained' part due to gender differences in the remuneration of these covariates, that is in gender differences in these covariates' coefficients (for a detailed discussion, see Fortin et al., 2011).

Following Firpo et al. (2009), the OB decompositions for the unconditional quantiles are based on two separate recentred influence function (RIF) regressions for the respective quantile for men and women. However, we do not perform the OB decomposition directly on the two RIFs because the linear approximation involved in using the RIFs is only locally valid and may thus result in a poor approximation and a large specification error for large gender differences in covariates. Instead, we follow Firpo et al.'s (2018) suggestion and perform all OB decompositions after reweighting the distribution of women's covariates to that of men. To arrive at this counterfactual sample, we apply the reweighting approach by DiNardo et al. (1996), which involves estimating the propensity score that we obtain from a logit model with the same covariates as in the RIF regressions (detailed in the next paragraph) and additional powers and interaction terms.[7]

To check whether non-base compensation contributes to the GPG, we include the bonus-to-income ratio as well as dummies for shift premia and overtime pay in the OB decompositions. The latter forms of non-base compensation enter as dummies because they are not that widespread and also rather modest in size for the vast majority of workers.[8] As further covariates we add the following groups of variables: (i) human capital variables capturing workers' educational attainment (distinguishing high-skilled workers with an academic education, medium-skilled workers with a vocational training, and low-skilled workers with neither), age (linearly and squared), and tenure (linearly and squared); (ii) job characteristics including groups of dummies for two-digit sectors, two-digit occupations, firm size, and workplace size, as well as dummies for working full-time hours, a temporary contract, and job location in East Germany; (iii) dummies for hierarchy levels (distinguishing the five hierarchy levels already mentioned and detailed in Appendix A); and (iv) a dummy for the existence of a collective agreement (either at sector or firm level).[9]

4 | DECOMPOSITION RESULTS

Table 4 presents the key findings of our OB decompositions of workers' log gross hourly wages (including non-base compensation), where we note in passing that these do not deviate in

TABLE 4 Oaxaca–Blinder decompositions of log gross hourly wages along the unconditional wage distribution

	Mean	%	p10	%	p25	%	p50	%	p75	%	p90	%
Raw differential	0.255 (0.00441)	*100*	0.154 (0.00379)	*100*	0.226 (0.00486)	*100*	0.213 (0.00556)	*100*	0.306 (0.00800)	*100*	0.377 (0.00643)	*100*
Explained part	0.145 (0.00581)	*57*	0.0508 (0.00518)	*33*	0.0975 (0.00600)	*43*	0.105 (0.00733)	*49*	0.184 (0.00908)	*60*	0.293 (0.0149)	*78*
thereof...												
Bonus-to-income ratio	0.0261 (0.00201)	*10*	0.0109 (0.000977)	*7*	0.0221 (0.00181)	*10*	0.0253 (0.00204)	*12*	0.0231 (0.00204)	*8*	0.0338 (0.00318)	*9*
Shift premium (0/1)	0.00339 (0.000391)	*1*	0.00551 (0.000667)	*4*	0.00527 (0.000661)	*2*	0.00312 (0.000440)	*1*	0.00222 (0.000383)	*1*	−0.000315 (0.000323)	*0*
Overtime pay (0/1)	0.000229 (0.000223)	*0*	−0.000796 (0.000413)	*−1*	−0.000505 (0.000398)	*0*	0.000974 (0.000324)	*0*	0.0000901 (0.000332)	*0*	0.000871 (0.000485)	*0*
Human capital	0.00431 (0.000859)	*2*	0.00206 (0.000575)	*1*	0.00330 (0.000777)	*1*	0.00484 (0.00111)	*2*	0.00551 (0.00118)	*2*	0.00662 (0.00129)	*2*
Job characteristics	0.0679 (0.00347)	*27*	0.0297 (0.00475)	*19*	0.0559 (0.00478)	*25*	0.0465 (0.00470)	*22*	0.0941 (0.00644)	*31*	0.141 (0.0113)	*37*
Hierarchy levels	0.0443 (0.00153)	*17*	0.00498 (0.000685)	*3*	0.0141 (0.00113)	*6*	0.0283 (0.00153)	*13*	0.0603 (0.00225)	*20*	0.110 (0.00431)	*29*
Collective agreement	−0.00172 (0.000529)	*−1*	−0.00154 (0.000505)	*−1*	−0.00266 (0.000848)	*−1*	−0.00406 (0.00125)	*−2*	−0.00155 (0.000484)	*−1*	0.00101 (0.000393)	*0*
Unexplained part	0.102 (0.00274)	*40*	0.0892 (0.00542)	*58*	0.0992 (0.00555)	*44*	0.0971 (0.00497)	*46*	0.105 (0.00549)	*34*	0.120 (0.00635)	*32*
Reweighting error	0.00334 (0.00353)	*1*	0.00981 (0.00365)	*6*	0.0136 (0.00449)	*6*	0.00710 (0.00467)	*3*	−0.00377 (0.00495)	*−1*	−0.00676 (0.00435)	*−2*
Specification error	0.00517 (0.00162)	*2*	0.00381 (0.00474)	*2*	0.0159 (0.00531)	*7*	0.00390 (0.00438)	*2*	0.0207 (0.00602)	*7*	−0.0285 (0.0125)	*−8*

Note: VSE 2014. OB decompositions based on OLS and RIF regressions with men as reference category. Bootstrapped (500 replications) standard errors clustered at the firm level in parentheses. RIF decompositions follow Firpo et al.'s (2018) two-step approach that performs the RIF decomposition after reweighting the distribution of covariates of women to that of men. The reweighting involves estimating the propensity score in a logit model including all covariates from the RIF regressions and additional powers and interaction terms. Included covariates in the OLS and RIF regressions are (i) human capital variables capturing workers' educational attainments, age (linearly and squared), and tenure (linearly and squared); (ii) job characteristics including groups of dummies for two-digit sectors, two-digit occupations, firm size, and workplace size as well as dummies for working full-time hours, a temporary contract, and job location in East Germany; (iii) dummies for hierarchy levels; and (iv) a dummy for the existence of a collective agreement.

Abbreviations: OB, Oaxaca–Blinder; OLS, ordinary least square; RIF, recentred influence function.

general terms from the results based on the VSE 2010 reported in Collischon (2019). At the mean of the unconditional wage distribution, 57 per cent of the GPG of 25.5 log points can be attributed to the included covariates.[10] Among the different forms of non-base compensation, gender differences in the bonus-to-income ratio are an important contributor to the mean GPG in that they explain 2.6 log points or 10 per cent of the mean GPG.[11] In contrast, gender differences in the prevalence of shift premia or overtime pay contribute little.

Like shift premia and overtime pay, human capital variables and collective bargaining coverage play only a minor role, which is in line with many recent studies (e.g., Goldin, 2014; Oberfichtner et al., 2020). Also in line with previous evidence, gender differences in job characteristics and in hierarchy levels contribute markedly to the mean GPG in that they explain 6.8 log points (27 per cent) or 4.4 log points (17 per cent), respectively.

Turning to the GPG at other points of the unconditional wage distribution, we observe that the contribution of gender differences in the bonus-to-income ratio to the GPG rises from 1.1 log points at the first decile to 3.4 log points at the ninth decile. As the GPG more than doubles from 15.4 log points to 37.7 log points when moving from the first decile to the ninth decile, gender differences in bonuses contribute significantly to the GPG along the whole wage distribution with a pretty stable relative contribution in between 7 per cent and 12 per cent of the GPG at the respective quantile.

This finding contrasts with other forms of non-base compensation that explain only little of the GPG. Although 0.6 (0.5) log points or 4 per cent (2 per cent) of the GPG is attributable to gender differences in the prevalence of shift premia at the first decile (quartile) of the wage distribution, which thus contribute somewhat to sticky floors, we see no contribution in the middle and the upper part of the wage distribution. And the contribution of less frequent overtime pay among women than men is nil over the entire wage distribution.

Turning to the other covariates in our RIF decompositions, we observe that gender differences in job characteristics explain 3 log points of the GPG at the first decile but 14 log points at the ninth decile and thus a rising fraction of the GPG of 19 per cent at the first and 37 per cent at the ninth decile. This rising contribution along the wage distribution is even more pronounced for hierarchy levels that explain 0.5 log points or 3 per cent of the GPG at the first decile, but 11 log points or 29 per cent at the ninth decile. This latter finding means that the underrepresentation of women in higher hierarchy levels with higher wages disproportionately contributes to the GPG in the upper part of the wage distribution, in line with glass ceilings stemming from discriminatory promotion practices against women, but also in line with women being less career-oriented than men.

Given the high and rising contribution of bonus payments, job characteristics, and hierarchy levels to the GPG in the upper quantiles, we find that the unexplained part of the GPG shrinks as we move upward the wage distribution. We further see that reweighting errors are small in size in all decompositions (and even statistically insignificant most of the time) and that they are also accompanied by modest specification errors, which points at a good quality of the reweighting procedure and little deviations from the local linearity assumption inherent to the RIF regressions.

One concern with our wage decomposition results is that our sample includes part-time workers who are less likely to receive (substantial) bonuses (see also Table B1) and who are more often women. Hence, our results may reflect, at least to some extent, gender differences in chosen working hours. In a check of robustness, we therefore perform the wage decompositions for the subsample of full-time workers. Reassuringly, our results for the bonus-to-income ratio are virtually the same when considering full-time workers (see Table D1), for whom working hours differences are of minor importance.

We also note in passing that our findings remain robust when restricting to further subsamples (results available upon request): They show up when considering separate samples for East Germany and West Germany, for workers covered by collective wage agreements and uncovered workers, and for workers employed in manufacturing and services. Finally, our results change little when performing the OB decomposition on the ordinary least square (OLS) and RIF regressions directly, that is when omitting the first-step reweighting procedure suggested by Firpo et al. (2018).

So far, we found clear evidence that bonus payments are an important source of the GPG whose absolute contribution to the GPG is rising as we move up the wage distribution and whose relative contribution is more or less constant around 10 per cent. In our descriptive analysis, we also saw that bonus payments are more prevalent and more sizeable in top hierarchy levels and differ more between men and women there than in the lower ranks which suggests that gender differences in bonus payments are likely to explain an even bigger part of the GPG among the higher echelons. To check this suggestion, we now present OB decompositions akin to those of Table 4 separately for the subgroups of managers and specialists, that is the two highest hierarchy levels in our data that comprise roughly a quarter of the workers in our sample.

Table 5 reports the OB decomposition for managers, that is for workers at the top hierarchy level comprising 8 per cent of workers in our sample. As we saw earlier in the descriptive findings, the GPG is much larger for the subgroup of managers compared with all other groups of workers and amounts to 28.6 log points at the mean. It also rises when moving up the wage distribution from 26.1 log points at the first decile to 35.1 log points at the ninth decile. The included covariates explain roughly half of the mean GPG, and gender differences in the bonus-to-income ratio stand out as the single most important contributor of 6.5 log points or 23 per cent to the mean GPG. Second comes gender differences in job characteristics that explain 6.4 log points or 22 per cent of the mean GPG, and third, gender differences in human capital that contribute 2.5 log points or 9 per cent. As was the case for all workers, non-base compensation in form of shift premia and overtime pay are unimportant.

What is more, for managers bonus payments disproportionately contribute to the GPG in the upper part of the unconditional wage distribution. Both their absolute and their relative contribution to the GPG steadily rises as we move to higher quantiles. Whereas gender differences in the bonus-to-income ratio explain 3.3 log points or 13 per cent of the GPG at the first decile, they explain even 11.8 log points or about a third of the GPG at the ninth decile. Notably, gender differences in bonuses are the most important contributor to the GPG once we move to the third quartile of the wage distribution and amount to almost two thirds of the explained part of the GPG at the ninth decile. In other words, at this top of the top gender differences in base salaries attributable to worker and job characteristics make up just one third of the explained GPG. This finding is clearly in line with glass ceilings in bonuses that translate into glass ceilings in total pay. And it is also in line with the notion that employers use their larger discretion over bonus payments compared with base salaries to discriminate against women as well as with the notion of men negotiating harder than women over bonuses.

Turning to the second highest hierarchy level, that is specialists who make up 17 per cent of workers in our sample, Table 6 shows that the patterns found for managers are mostly group-specific. For specialists, gender differences in the bonus-to-income ratio explain 2.1 log points or 12 per cent of the mean GPG of 18.4 log points. This is roughly half of the relative contribution of bonuses to the mean GPG found for managers in Table 5 and about a third of the contribution of job characteristics to the mean GPG of specialists, which explain 6.1 log points or

TABLE 5 Oaxaca–Blinder decomposition of log gross hourly wages of managers along the unconditional wage distribution

	Mean	%	p10	%	p25	%	p50	%	p75	%	p90	%
Raw differential	0.286 (0.00763)	*100*	0.261 (0.0140)	*100*	0.279 (0.0125)	*100*	0.263 (0.00893)	*100*	0.290 (0.00988)	*100*	0.351 (0.0151)	*100*
Explained part	0.152 (0.0102)	*53*	0.115 (0.0110)	*44*	0.130 (0.0127)	*47*	0.146 (0.0116)	*56*	0.151 (0.0124)	*52*	0.194 (0.0211)	*55*
thereof...												
Bonus-to-income ratio	0.0645 (0.00817)	*23*	0.0333 (0.00501)	*13*	0.0384 (0.00522)	*14*	0.0412 (0.00619)	*16*	0.0589 (0.00777)	*20*	0.118 (0.0150)	*34*
Shift premium (0/1)	−0.000611 (0.000452)	*0*	0.00159 (0.00114)	*1*	0.000754 (0.000770)	*0*	−0.00314 (0.000825)	*−1*	−0.000798 (0.000655)	*0*	0.000199 (0.00103)	*0*
Overtime pay (0/1)	−0.000144 (0.000185)	*0*	−0.000208 (0.000282)	*0*	−0.000201 (0.000259)	*0*	−0.000102 (0.000194)	*0*	−0.000204 (0.000275)	*0*	−0.000212 (0.000330)	*0*
Human capital	0.0252 (0.00220)	*9*	0.0181 (0.00325)	*7*	0.0262 (0.00308)	*9*	0.0312 (0.00278)	*12*	0.0269 (0.00249)	*9*	0.0265 (0.00360)	*8*
Job characteristics	0.0636 (0.00629)	*22*	0.0723 (0.0103)	*28*	0.0784 (0.0100)	*28*	0.0807 (0.00870)	*31*	0.0571 (0.00813)	*20*	0.0324 (0.0111)	*9*
Collective agreement	−0.000733 (0.000772)	*0*	−0.0102 (0.00214)	*−4*	−0.0137 (0.00237)	*−5*	−0.00346 (0.00111)	*−1*	0.00921 (0.00186)	*3*	0.0165 (0.00371)	*5*
Unexplained part	0.119 (0.00728)	*42*	0.118 (0.0169)	*45*	0.132 (0.00966)	*47*	0.112 (0.00726)	*43*	0.130 (0.0110)	*45*	0.135 (0.0152)	*38*
Reweighting error	0.00355 (0.0107)	*1*	0.00922 (0.00943)	*4*	0.0108 (0.00648)	*4*	0.0102 (0.00645)	*4*	−0.00120 (0.0107)	*0*	−0.0138 (0.0171)	*−4*
Specification error	0.0118 (0.00567)	*4*	0.0191 (0.0129)	*7*	0.00686 (0.00834)	*2*	−0.00619 (0.00682)	*−2*	0.0102 (0.00897)	*4*	0.0364 (0.0191)	*10*

Note: VSE 2014. OB decompositions based on OLS and RIF regressions with men as reference category. Bootstrapped (500 replications) standard errors clustered at the firm level in parentheses. RIF decompositions follow Firpo et al.'s (2018) two-step approach that performs the RIF decomposition after reweighting the distribution of covariates of women to that of men. The reweighting involves estimating the propensity score in a logit model including all covariates from the RIF regressions and additional powers and interaction terms. Included covariates in the OLS and RIF regressions are (i) human capital variables capturing workers' educational attainments, age (linearly and squared), and tenure (linearly and squared); (ii) job characteristics including groups of dummies for two-digit sectors, two-digit occupations, firm size, and workplace size as well as dummies for working full-time hours, a temporary contract, and job location in East Germany; and (iii) a dummy for the existence of a collective agreement.

Abbreviations: OB, Oaxaca–Blinder; OLS, ordinary least square; RIF, recentred influence function.

TABLE 6 Oaxaca–Blinder decompositions of log gross hourly wages of specialists along unconditional wage distribution

	Mean	%	p10	%	p25	%	p50	%	p75	%	p90	%
Raw differential	0.184 (0.00500)	*100*	0.151 (0.00666)	*100*	0.153 (0.00592)	*100*	0.185 (0.00553)	*100*	0.225 (0.00762)	*100*	0.202 (0.00840)	*100*
Explained part	0.0915 (0.00670)	*50*	0.0499 (0.0118)	*33*	0.0561 (0.00811)	*37*	0.0924 (0.00760)	*50*	0.136 (0.0112)	*60*	0.138 (0.0164)	*68*
thereof...												
Bonus-to-income ratio	0.0213 (0.00278)	*12*	0.0169 (0.00241)	*11*	0.0148 (0.00213)	*10*	0.0152 (0.00202)	*8*	0.0226 (0.00321)	*10*	0.0329 (0.00463)	*16*
Shift premium (0/1)	0.000591 (0.000286)	*0*	0.00144 (0.000678)	*1*	0.000583 (0.000419)	*0*	0.0000775 (0.000267)	*0*	0.000423 (0.000341)	*0*	0.000239 (0.000394)	*0*
Overtime pay (0/1)	−0.00000575 (0.000322)	*0*	0.000278 (0.000615)	*0*	−0.000250 (0.000430)	*0*	0.000255 (0.000374)	*0*	0.000300 (0.000491)	*0*	0.000699 (0.000853)	*0*
Human capital	0.00836 (0.00155)	*5*	0.00920 (0.00179)	*6*	0.00769 (0.00167)	*5*	0.00715 (0.00171)	*4*	0.00929 (0.00170)	*4*	0.00946 (0.00177)	*5*
Job characteristics	0.0606 (0.00555)	*33*	0.0357 (0.0111)	*24*	0.0428 (0.00682)	*28*	0.0716 (0.00646)	*39*	0.0955 (0.0102)	*42*	0.0751 (0.0156)	*37*
Collective agreement	0.000637 (0.000628)	*0*	−0.0136 (0.00223)	*−9*	−0.00958 (0.00155)	*−6*	−0.00192 (0.000687)	*−1*	0.00812 (0.00158)	*4*	0.0199 (0.00309)	*10*
Unexplained part	0.0863 (0.00546)	*47*	0.0930 (0.0126)	*62*	0.0800 (0.0104)	*52*	0.0884 (0.00666)	*48*	0.0838 (0.0117)	*37*	0.0946 (0.0109)	*47*
Reweighting error	−0.000136 (0.00441)	*0*	0.00442 (0.00876)	*3*	0.00667 (0.00748)	*4*	−0.00279 (0.00564)	*−2*	−0.00144 (0.00544)	*−1*	−0.00513 (0.00551)	*−3*
Specification error	0.00625 (0.00286)	*3*	0.00343 (0.00882)	*2*	0.0108 (0.00719)	*7*	0.00680 (0.00517)	*4*	0.00608 (0.00891)	*3*	−0.0257 (0.0116)	*−13*

Note: VSE 2014. OB decompositions based on OLS and RIF regressions with men as reference category. Bootstrapped (500 replications) standard errors clustered at the firm level in parentheses. RIF decompositions follow Firpo et al.'s (2018) two-step approach that performs the RIF decomposition after reweighting the distribution of covariates of women to that of men. The reweighting involves estimating the propensity score in a logit model including all covariates from the RIF regressions and additional powers and interaction terms. Included covariates in the OLS and RIF regressions are (i) human capital variables capturing workers' educational attainments, age (linearly and squared), and tenure (linearly and squared); (ii) job characteristics including groups of dummies for two-digit sectors, two-digit occupations, firm size, and workplace size as well as dummies for working full-time hours, a temporary contract, and job location in East Germany; and (iii) a dummy for the existence of a collective agreement.

Abbreviations: OB, Oaxaca–Blinder; OLS, ordinary least square; RIF, recentred influence function.

33 per cent. Furthermore, when moving along the wage distribution gender differences in bonus payments explain roughly 10 per cent of the GPG at all the quantiles considered. The only exception is the ninth decile where their contribution of 3.3 log points or 16 per cent to the GPG is more pronounced but still substantially lower than their contribution to the GPG of managers at the ninth decile (11.8 log points or 34 per cent).[12]

5 | DISCUSSION

How do our findings relate to the existing evidence on the influence of bonus payments on the GPG? And what are possible *caveats* about our findings?

As we saw in the introduction, there exist, to the best of our knowledge, only two papers that explicitly investigate how bonuses shape the GPG and these exclusively focus on workers in top jobs. Examining executive directors of UK-listed firms, Kulich et al. (2011) find a descriptive median GPG of 19 per cent and a substantially larger median gender gap in bonuses of 36 per cent. What is more, bonuses paid to women are not only smaller in absolute terms than those paid to men, but also in relative terms, with bonuses amounting to 24 per cent (27 per cent) of women's (men's) base salaries at the median. Investigating middle managers in the German chemical sector, Grund (2015) documents an average GPG of 22 per cent and an average gender gap in bonuses of 46 per cent. In OLS regressions that control for a large array of individual and job characteristics, he further shows that women receive 8 per cent less bonuses than men on average, but only 3 per cent less fixed salaries, implying a larger GPG for higher bonus-to-income ratios.

Overall, these previous findings for workers in top jobs nicely square up with our findings for the much broader population of workers at all hierarchy levels. They are further consistent with our findings for workers at the top of the hierarchy, though we find, in contrast to a robustness check by Grund (2015) based on conditional quantile regressions, clear evidence of a widening of the GPG when moving up the wage distribution (both for all workers and for workers in top jobs).

Turning to possible *caveats* about our findings and our suggested interpretation of them in terms of glass ceilings, we already discussed the problem that gender differences in bonuses may to some extent originate from differences in working hours that, in turn, are partly chosen by workers. Since restricting to full-time workers did not change our estimates, we think this issue is of little concern. Somewhat related, though, gender differences in bonuses may stem from performance differences unobserved by the econometrician. Hence, their contribution to the GPG could reflect such performance differences rather than discriminatory practices and vertical segregation, and we acknowledge this possibility, which we unfortunately cannot rule out with our data.

One further *caveat* is that our data do not contain information on parental leave periods and thus prevent us from correcting workers' job tenure for such career interruptions. This does not only mean that our data tend to overstate women's tenure relative to men's, but it may also affect our results because Gerst and Grund (2022) document, in a follow-up paper to Grund (2015), that parental leave periods widen both the mean GPG and the mean gender gap in bonuses. Although our feeling is that the potential for severe bias is limited in our application, our data do not allow us to explore this issue further. In particular, the VSE data do not include information on workers' family status that would have permitted us to check how our results vary with workers' number of children.

6 | CONCLUSION

Using German linked employer–employee data from the mandatory Structure of Earnings Survey for the year 2014, this paper has investigated how gender differences in non-base compensation influence the GPG. To that end, we analysed the contribution of bonus payments, shift premia, and overtime pay to the mean GPG and to the GPGs along the unconditional wage distribution.

Descriptively, we saw that women are less likely to receive bonus payments and also receive less sizeable bonuses. The same pattern also showed up for shift premia and overtime pay, but these forms of non-base compensation are much more limited in prevalence as is, in consequence, their scope to contribute substantially to the GPG. We further observed that the GPG is more pronounced when wages include bonus payments and that the difference in the GPG from the inclusion of bonuses is larger in higher hierarchy levels and at higher quantiles of the wage distribution.

In wage decompositions, we found that gender differences in bonus payments are an important contributor to the GPG both at the mean and along the unconditional wage distribution. They explain about 10 per cent of the mean GPG and the GPG at several quantiles of the wage distribution. That said, their absolute contribution rises over the wage distribution as does the GPG, where the latter finding is consistent with glass ceilings. Further in line with glass ceilings, gender differences in bonuses are much more important for managers at the top of the hierarchy, and their absolute and their relative contribution to managers' GPG also steadily rises as one moves up the wage distribution. What is more, they stand out as the most important contributor to the GPG at the top of the top in that they explain almost two thirds of managers' GPG at the ninth decile of the wage distribution.

In short, our results show that gender differences in bonus payments contribute substantially to the GPG, and they are clearly in line with glass ceilings in the form of much more pronounced gender differences in bonuses in top jobs. These may reflect employers' larger discretion over bonus payments compared with base salaries that leaves women in top jobs particularly vulnerable to discrimination, but may also mirror that 'women do not ask' (Babcock & Laschever, 2003) and realize inferior outcomes in negotiations, which are more likely to take place in top jobs. That said, our data did not allow us to rule out that gender differences in bonuses may also stem from performance differences rather than discriminatory practices. Settling this issue is a promising avenue for further research.

As Goldin (2014) notes, women's job decisions continue to shift toward more remunerative and career-oriented fields. We expect this ongoing trend to further increase the important role of bonus payments for the GPG documented in this paper. Unfortunately, our data did not permit us to analyse specific components of bonus payments, such as stock options, incentive bonuses, and profit sharing. Such a detailed analysis promises additional insights why bonus payments are lower for women than for men and on the specific channels how they contribute to the GPG, and potential glass ceilings in particular.

ACKNOWLEDGMENTS

The authors thank Luise Görges, Christian Pfeifer, Claus Schnabel, Thomas Zwick, two anonymous referees, and the editor for useful suggestions. The authors further appreciate comments by participants of the 13th IAAEU Workshop on Labour Economics in Trier and the GRAPE 2021 Gender Gaps Conference as well as by seminar participants in Lüneburg and Nuremberg. Open Access funding enabled and organized by Projekt DEAL.

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ENDNOTES

[1] The exception is a negligible number of workers with exceptionally high wages, that is, a yearly remuneration exceeding €750,000, that are censored and that we exclude from our sample.

[2] Note that the VSE data do not contain information on parental leave periods, so tenure is just the elapsed time since firm entry. We will return to this issue later when discussing our results in Section 5.

[3] For more details on the prevalence of bonus payments, see Appendix B.

[4] Specifically, the bonus-to-income ratio is the ratio of worker's yearly bonus payments and his or her total yearly earnings including bonus payments and other non-base compensation.

[5] Note that we obtain similar patterns when distinguishing high-skilled workers with an academic education, medium-skilled workers with a vocational training, and low-skilled workers with neither. That is, the GPG is larger in the upper part of the wage distribution, for higher skill levels, and in the upper part of the wage distribution within skill levels, and even more so when wages include bonus payments (see Table C1).

[6] That said, we cannot rule out that these descriptive patterns are, for example, driven by job heterogeneities within hierarchy levels and correlations of hierarchy levels with firm characteristics, such as firm size. However, this should be less of a concern in our multivariate wage decompositions that account for a large array of job and firm characteristics.

[7] Calculations are done in `Stata 16.1` using the ado-files by Rios-Avila (2020).

[8] As a check of robustness, we also perform wage decompositions in which all three types of non-base compensation are included either as income ratios or as dummy variables. In the former specification reported in Table D2, we get almost the same findings as in our baseline specification reported in Table 4. In the latter specification reported in Table D3, the contribution of the dummy variable for bonus payments to the 'explained' part of the GPG is generally lower than the contribution of the bonus-to-income ratio in our baseline specification. This finding, however, is hardly surprising against the background that the vast majority of workers in our sample, men and women alike, receive some bonus payments, so that the intensive margin of bonuses captured by the bonus-to-income ratio is arguably more important than their extensive margin captured by the dummy variable.

[9] Note that we employ the normalization procedure by Yun (2005) for those dummies reflecting categorial variables with more than two values.

[10] Given our large sample size, we will in the following abstain from commenting on statistical significance and focus on effect sizes instead.

[11] When interpreting this finding note that the bonus-to-income ratio measures the share of bonuses in workers' hourly wage including these bonuses and other non-base compensation and thus only captures the composition of workers' salaries in terms of bonuses. This means, in particular, that a higher bonus-to-income ratio does not imply a higher wage and that there is no mechanical relationship between the bonus-to-income ratio and wages or workers' position in the wage distribution.

[12] Note that we get very similar results when running wage decompositions for the group of high-skilled workers (reported in Table D4), which one should have expected given that about two-thirds of workers with an academic education work at the top of the hierarchy and specialists clearly outnumber managers in our sample.

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APPENDIX A: HIERARCHY LEVELS

The hierarchy level information in the VSE 2014 takes on five values ranges from working 'simple tasks' to 'managerial duties.' Workers are assigned into these groups based on the operational grouping in the collective agreement or if there is no coverage based on the definitions given in the VSE as follows:

Hierarchy level 1 'managerial duties' comprise: 'Workers in leading positions with supervisory and disposition powers. These also comprise, for example, salaried managing directors, provided that their earnings at least partially include payments that are independent of success. Also included are all workers who perform disposition or management tasks in larger management areas (e.g., heads of department) and workers with activities that require extensive commercial or technical expertise.'

Hierarchy level 2 'specialists' comprise: 'Workers with very difficult to complex or multifaceted activities that usually require a completed vocational training and several years of work experience as well as special expertise. These activities are predominantly carried out independently. In addition also workers who hold responsibility in small areas or for other coworkers.'

Hierarchy level 3 'experienced workers' comprise: 'Workers with difficult specialist activities that usually require a completed vocational training, sometimes combined with work experience.'

Hierarchy level 4 'no decision-making responsibilities' comprise: 'Semi-skilled workers with predominantly simple activities that do not require a vocational training but special knowledge and skills for special, industry-related tasks. The necessary knowledge and skills are usually acquired through a training period of up to 2 years.'

Hierarchy level 5 'simple tasks' comprise: 'Unskilled workers with simple, schematic activities or isolated work processes that do not require a vocational training. The necessary knowledge and skills can be acquired by a training of up to 3 months.'

APPENDIX B: FURTHER DESCRIPTIVE FINDINGS ON BONUS PAYMENTS

Since only few papers investigate bonus payments in detail, this appendix provides some additional descriptive findings on the prevalence of this non-base remuneration component. As is seen from Table B1, bonus payments are more widespread in West Germany than in East Germany, with 71 per cent of West German but just 60 per cent of East German workers receiving at least one yearly bonus payment. They are further more prevalent in the manufacturing than in the services industries (83 per cent vs. 66 per cent of workers) and in large companies than in small firms. Moreover, 88 per cent of workers covered by collective bargaining receive bonus payments compared with just 58 per cent of uncovered workers. Finally, they are more widespread among high-wage than among low-wage workers, with 86 per cent of workers with above-median wages receiving bonus payments but only 52 per cent of workers with below-median wages.

TABLE B1 Prevalence of bonus payments

West Germany	71%
East Germany	60%
Manufacturing	83%
Services	66%
Full-time employment	74%
Part-time employment	60%
Firm size	
<50 workers	47%
50–249 workers	74%
250 and more workers	89%
Worker covered by collective bargaining	88%
Worker uncovered by collective bargaining	58%
Worker with above-median wage	86%
Worker with below-median wage	52%

Note: VSE 2014, weighted using sample weights.

APPENDIX C: GENDER PAY GAP BY WORKERS' EDUCATIONAL ATTAINMENT

TABLE C1 Gender pay gaps in gross hourly wages along the wage distribution

	Mean	p10	p25	p50	p75	p90
Excluding bonus payments						
Overall	23%	12%	16%	17%	24%	31%
High skill	27%	24%	24%	26%	26%	26%
Medium skill	17%	12%	13%	12%	16%	23%
Low skill	17%	1%	6%	15%	17%	23%
Including bonus payments						
Overall	26%	12%	16%	17%	26%	33%
High skill	30%	24%	25%	28%	29%	31%
Medium skill	18%	12%	13%	12%	17%	25%
Low skill	18%	1%	7%	14%	18%	24%

Note: VSE 2014, weighted using sample weights.

APPENDIX D: FURTHER MULTIVARIATE FINDINGS FROM WAGE DECOMPOSITIONS

TABLE D1 Oaxaca–Blinder decompositions of log gross hourly wages of full-time workers along the unconditional wage distribution

	Mean	%	p10	%	p25	%	p50	%	p75	%	p90	%
Raw differential	0.226 (0.00450)	*100*	0.186 (0.00386)	*100*	0.202 (0.00516)	*100*	0.186 (0.00567)	*100*	0.259 (0.00779)	*100*	0.307 (0.00650)	*100*
Explained part	0.131 (0.00596)	*58*	0.0694 (0.00596)	*37*	0.105 (0.00724)	*52*	0.0967 (0.00709)	*52*	0.160 (0.00915)	*62*	0.229 (0.0134)	*75*
thereof...												
Bonus-to-income ratio	0.0264 (0.00211)	*12*	0.0113 (0.00103)	*6*	0.0208 (0.00176)	*10*	0.0221 (0.00200)	*12*	0.0236 (0.00202)	*9*	0.0385 (0.00329)	*13*
Shift premium (0/1)	0.00322 (0.000397)	*1*	0.00627 (0.000854)	*3*	0.00498 (0.000776)	*2*	0.00348 (0.000527)	*2*	0.000668 (0.000414)	*0*	−0.000311 (0.000486)	*0*
Overtime pay (0/1)	−0.000848 (0.000354)	*0*	−0.00184 (0.000862)	*−1*	−0.00191 (0.000709)	*−1*	−0.00109 (0.000529)	*−1*	0.000685 (0.000619)	*0*	0.00169 (0.000924)	*1*
Human capital	0.0179 (0.000980)	*8*	0.0101 (0.000821)	*5*	0.0160 (0.00106)	*8*	0.0203 (0.00117)	*11*	0.0198 (0.00117)	*8*	0.0180 (0.00117)	*6*
Job characteristics	0.0524 (0.00371)	*23*	0.0386 (0.00550)	*21*	0.0533 (0.00577)	*26*	0.0296 (0.00496)	*16*	0.0702 (0.00645)	*27*	0.0941 (0.0103)	*31*
Hierarchy levels	0.0305 (0.00176)	*13*	0.00359 (0.000936)	*2*	0.00934 (0.00140)	*5*	0.0192 (0.00148)	*10*	0.0439 (0.00255)	*17*	0.0785 (0.00446)	*26*
Collective agreement	0.00133 (0.000504)	*1*	0.00143 (0.000560)	*1*	0.00278 (0.00107)	*1*	0.00308 (0.00118)	*2*	0.00108 (0.000434)	*0*	−0.00171 (0.000683)	*−1*
Unexplained part	0.106 (0.00300)	*47*	0.117 (0.00531)	*63*	0.107 (0.00610)	*53*	0.0957 (0.00615)	*51*	0.106 (0.00569)	*41*	0.125 (0.00649)	*41*
Reweighting error	−0.0140 (0.00350)	*−6*	−0.00537 (0.00423)	*−3*	−0.00858 (0.00480)	*−4*	−0.0135 (0.00515)	*−7*	−0.0195 (0.00444)	*−8*	−0.0180 (0.00413)	*−6*
Specification error	0.00273 (0.00145)	*1*	0.00530 (0.00425)	*3*	−0.00155 (0.00518)	*−1*	0.00695 (0.00478)	*4*	0.0130 (0.00581)	*5*	−0.0290 (0.00927)	*−9*

Note: VSE 2014. OB decompositions based on OLS and RIF regressions with men as reference category. Bootstrapped (500 replications) standard errors clustered at the firm level in parentheses. RIF decompositions follow Firpo et al.'s (2018) two-step approach that performs the RIF decomposition after reweighting the distribution of covariates of women to that of men. The reweighting involves estimating the propensity score in a logit model including all covariates from the RIF regressions and additional powers and interaction terms. Included covariates in the OLS and RIF regressions are (i) human capital variables capturing workers' educational attainments, age (linearly and squared), and tenure (linearly and squared); (ii) job characteristics including groups of dummies for two-digit sectors, two-digit occupations, firm size, and workplace size as well as a dummy for a temporary contract, and job location in East Germany; (iii) dummies for hierarchy levels; and (iv) a dummy for the existence of a collective agreement.

Abbreviations: OB, Oaxaca–Blinder; OLS, ordinary least square; RIF, recentred influence function.

TABLE D2 Oaxaca–Blinder decompositions of log gross hourly wages along the unconditional wage distribution (ratio specification)

	Mean	%	p10	%	p25	%	p50	%	p75	%	p90	%
Raw differential	0.255 (0.00451)	*100*	0.154 (0.00389)	*100*	0.226 (0.00463)	*100*	0.213 (0.00534)	*100*	0.306 (0.00797)	*100*	0.377 (0.00658)	*100*
Explained part	0.146 (0.00671)	*57*	0.0511 (0.00505)	*33*	0.0986 (0.00607)	*44*	0.105 (0.00700)	*49*	0.187 (0.00889)	*61*	0.295 (0.0147)	*78*
thereof...												
Bonus-to-income ratio	0.0259 (0.00216)	*10*	0.0109 (0.000961)	*7*	0.0219 (0.00187)	*10*	0.0251 (0.00212)	*12*	0.0229 (0.00194)	*7*	0.0335 (0.00289)	*9*
Shift premium-to-income ratio	0.00650 (0.000673)	*3*	0.00778 (0.000882)	*5*	0.00859 (0.000965)	*4*	0.00559 (0.000648)	*3*	0.00659 (0.000769)	*2*	0.00341 (0.000616)	*1*
Overtime pay-to-income ratio	0.000204 (0.0000872)	*0*	−0.000280 (0.000174)	*0*	0.0000482 (0.000133)	*0*	0.000469 (0.000151)	*0*	0.000221 (0.000130)	*0*	0.000155 (0.000144)	*0*
Human capital	0.00427 (0.000917)	*2*	0.00194 (0.000572)	*1*	0.00319 (0.000796)	*1*	0.00480 (0.00114)	*2*	0.00553 (0.00123)	*2*	0.00666 (0.00126)	*2*
Job characteristics	0.0667 (0.00372)	*26*	0.0279 (0.00458)	*18*	0.0542 (0.00460)	*24*	0.0458 (0.00429)	*22*	0.0932 (0.00610)	*30*	0.140 (0.0110)	*37*
Hierarchy levels	0.0439 (0.00185)	*17*	0.00461 (0.000691)	*3*	0.0136 (0.00120)	*6*	0.0278 (0.00161)	*13*	0.0600 (0.00254)	*20*	0.110 (0.00446)	*29*
Collective agreement	−0.00190 (0.000544)	*−1*	−0.00176 (0.000510)	*−1*	−0.00294 (0.000842)	*−1*	−0.00439 (0.00125)	*−2*	−0.00168 (0.000490)	*−1*	0.00110 (0.000360)	*0*
Unexplained part	0.100 (0.00294)	*39*	0.0911 (0.00550)	*59*	0.0992 (0.00612)	*44*	0.0931 (0.00569)	*44*	0.101 (0.00602)	*33*	0.118 (0.00725)	*31*
Reweighting error	0.00336 (0.00549)	*1*	0.00988 (0.00468)	*6*	0.0132 (0.00579)	*6*	0.00651 (0.00648)	*3*	−0.00453 (0.00679)	*−1*	−0.00620 (0.00688)	*−2*
Specification error	0.00590 (0.00182)	*2*	0.00165 (0.00460)	*1*	0.0152 (0.00519)	*7*	0.00832 (0.00467)	*4*	0.0227 (0.00616)	*7*	−0.0293 (0.0102)	*−8*

Note: VSE 2014. OB decompositions based on OLS and RIF regressions with men as reference category. Bootstrapped (500 replications) standard errors clustered at the firm level in parentheses. RIF decompositions follow Firpo et al.'s (2018) two-step approach that performs the RIF decomposition after reweighting the distribution of covariates of women to that of men. The reweighting involves estimating the propensity score in a logit model including all covariates from the RIF regressions and additional powers and interaction terms. Included covariates in the OLS and RIF regressions are (i) human capital variables capturing workers' educational attainments, age (linearly and squared), and tenure (linearly and squared); (ii) job characteristics including groups of dummies for two-digit sectors, two-digit occupations, firm size, and workplace size as well as dummies for working full-time hours, a temporary contract, and job location in East Germany; (iii) dummies for hierarchy levels; and (iv) a dummy for the existence of a collective agreement.

Abbreviations: OB, Oaxaca–Blinder; OLS, ordinary least square; RIF, recentred influence function.

TABLE D3 Oaxaca–Blinder decompositions of log gross hourly wages along the unconditional wage distribution (dummy specification)

	Mean	%	p10	%	p25	%	p50	%	p75	%	p90	%
Raw differential	0.255 (0.00419)	*100*	0.154 (0.00378)	*100*	0.226 (0.00494)	*100*	0.213 (0.00586)	*100*	0.306 (0.00785)	*100*	0.377 (0.00640)	*100*
Explained part	0.133 (0.00581)	*52*	0.0442 (0.00495)	*29*	0.0865 (0.00599)	*38*	0.0940 (0.00699)	*44*	0.174 (0.00871)	*57*	0.280 (0.0137)	*74*
thereof...												
Bonus payment (0/1)	0.00471 (0.000946)	*2*	0.00573 (0.00114)	*4*	0.00777 (0.00151)	*3*	0.00534 (0.00109)	*3*	0.00236 (0.000482)	*1*	0.00132 (0.000304)	*0*
Shift premium (0/1)	0.00295 (0.000343)	*1*	0.00493 (0.000606)	*3*	0.00447 (0.000557)	*2*	0.00260 (0.000395)	*1*	0.00204 (0.000374)	*1*	−0.000374 (0.000348)	*0*
Overtime pay (0/1)	−0.00000461 (0.000216)	*0*	−0.00117 (0.000398)	*−1*	−0.000978 (0.000400)	*0*	0.000695 (0.000318)	*0*	0.0000134 (0.000338)	*0*	0.000916 (0.000508)	*0*
Human capital	0.00419 (0.000937)	*2*	0.00226 (0.000532)	*1*	0.00348 (0.000710)	*2*	0.00471 (0.00123)	*2*	0.00517 (0.00134)	*2*	0.00617 (0.00141)	*2*
Job characteristics	0.0786 (0.00417)	*31*	0.0285 (0.00450)	*19*	0.0595 (0.00473)	*26*	0.0559 (0.00476)	*26*	0.106 (0.00705)	*35*	0.162 (0.0122)	*43*
Hierarchy levels	0.0448 (0.00168)	*18*	0.00503 (0.000654)	*3*	0.0145 (0.00112)	*6*	0.0289 (0.00159)	*14*	0.0606 (0.00224)	*20*	0.110 (0.00417)	*29*
Collective agreement	−0.00185 (0.000543)	*−1*	−0.00102 (0.000342)	*−1*	−0.00219 (0.000704)	*−1*	−0.00407 (0.00129)	*−2*	−0.00193 (0.000615)	*−1*	0.000138 (0.000217)	*0*
Unexplained part	0.104 (0.00297)	*41*	0.0890 (0.00543)	*58*	0.0923 (0.00563)	*41*	0.0946 (0.00506)	*44*	0.107 (0.00584)	*35*	0.128 (0.00614)	*34*
Reweighting error	0.0108 (0.00367)	*4*	0.0151 (0.00407)	*10*	0.0208 (0.00455)	*9*	0.0130 (0.00456)	*6*	0.00224 (0.00474)	*1*	0.00000270 (0.00373)	*0*
Specification error	0.00698 (0.00168)	*3*	0.00535 (0.00506)	*3*	0.0265 (0.00527)	*12*	0.0116 (0.00436)	*5*	0.0222 (0.00597)	*7*	−0.0303 (0.0108)	*−8*

Note: VSE 2014. OB decompositions based on OLS and RIF regressions with men as reference category. Bootstrapped (500 replications) standard errors clustered at the firm level in parentheses. RIF decompositions follow Firpo et al.'s (2018) two-step approach that performs the RIF decomposition after reweighting the distribution of covariates of women to that of men. The reweighting involves estimating the propensity score in a logit model including all covariates from the RIF regressions and additional powers and interaction terms. Included covariates in the OLS and RIF regressions are (i) human capital variables capturing workers' educational attainments, age (linearly and squared), and tenure (linearly and squared); (ii) job characteristics including groups of dummies for two-digit sectors, two-digit occupations, firm size, and workplace size as well as dummies for working full-time hours, a temporary contract, and job location in East Germany; (iii) dummies for hierarchy levels; and (iv) a dummy for the existence of a collective agreement.

Abbreviations: OB, Oaxaca–Blinder; OLS, ordinary least square; RIF, recentred influence function.

TABLE D4 Oaxaca–Blinder decompositions of log gross hourly wages of high-skilled workers along the unconditional wage distribution

	Mean	%	p10	%	p25	%	p50	%	p75	%	p90	%
Raw differential	0.323 (0.00576)	*100*	0.291 (0.00957)	*100*	0.295 (0.00750)	*100*	0.327 (0.00740)	*100*	0.339 (0.00730)	*100*	0.353 (0.00896)	*100*
Explained part	0.200 (0.00814)	*62*	0.155 (0.00906)	*53*	0.158 (0.00818)	*54*	0.199 (0.00855)	*61*	0.245 (0.0112)	*72*	0.254 (0.0139)	*72*
thereof...												
Bonus-to-income ratio	0.0426 (0.00332)	*13*	0.0288 (0.00249)	*10*	0.0293 (0.00243)	*10*	0.0306 (0.00249)	*9*	0.0402 (0.00324)	*12*	0.0644 (0.00524)	*18*
Shift premium (0/1)	−0.000184 (0.000206)	*0*	−0.000269 (0.000308)	*0*	−0.000133 (0.000154)	*0*	−0.0000193 (0.0000416)	*0*	−0.000305 (0.000341)	*0*	−0.000182 (0.000209)	*0*
Overtime pay (0/1)	−0.0000493 (0.000121)	*0*	0.0000100 (0.000380)	*0*	−0.000438 (0.000212)	*0*	0.0000134 (0.000162)	*0*	0.000398 (0.000235)	*0*	−0.000268 (0.000317)	*0*
Human capital	0.0162 (0.000911)	*5*	0.00315 (0.00128)	*1*	0.0120 (0.00108)	*4*	0.0192 (0.00117)	*6*	0.0224 (0.00127)	*7*	0.0221 (0.00135)	*6*
Job characteristics	0.0787 (0.00461)	*24*	0.0845 (0.00697)	*29*	0.0763 (0.00557)	*26*	0.0870 (0.00529)	*27*	0.0954 (0.00814)	*28*	0.0800 (0.0101)	*23*
Hierarchy levels	0.0636 (0.00289)	*20*	0.0445 (0.00423)	*15*	0.0478 (0.00313)	*16*	0.0663 (0.00299)	*20*	0.0854 (0.00367)	*25*	0.0796 (0.00389)	*23*
Collective agreement	−0.00100 (0.000310)	*0*	−0.00530 (0.00133)	*−2*	−0.00635 (0.00156)	*−2*	−0.00371 (0.000934)	*−1*	0.00158 (0.000507)	*0*	0.00857 (0.00211)	*2*
Unexplained part	0.106 (0.00547)	*33*	0.102 (0.0149)	*35*	0.106 (0.00848)	*36*	0.113 (0.00783)	*35*	0.106 (0.00954)	*31*	0.119 (0.0135)	*34*
Reweighting error	0.0113 (0.00803)	*3*	0.0204 (0.0118)	*7*	0.0163 (0.00987)	*6*	0.0112 (0.00811)	*3*	0.00708 (0.00788)	*2*	0.00222 (0.0102)	*1*
Specification error	0.00630 (0.00316)	*2*	0.0130 (0.0134)	*4*	0.0140 (0.00754)	*5*	0.00266 (0.00658)	*1*	−0.0200 (0.00738)	*−6*	−0.0219 (0.0129)	*−6*

Note: VSE 2014. OB decompositions based on OLS and RIF regressions with men as reference category. Bootstrapped (500 replications) standard errors clustered at the firm level in parentheses. RIF decompositions follow Firpo et al.'s (2018) two-step approach that performs the RIF decomposition after reweighting the distribution of covariates of women to that of men. The reweighting involves estimating the propensity score in a logit model including all covariates from the RIF regressions and additional powers and interaction terms. Included covariates in the OLS and RIF regressions are (i) human capital variables capturing workers' age (linearly and squared), and tenure (linearly and squared); (ii) job characteristics including groups of dummies for two-digit sectors, two-digit occupations, firm size, and workplace size as well as dummies for working full-time hours, a temporary contract, and job location in East Germany; (iii) dummies for hierarchy levels; and (iv) a dummy for the existence of a collective agreement.

Abbreviations: OB, Oaxaca–Blinder; OLS, ordinary least square; RIF, recentred influence function.

Received: 3 December 2021 | Accepted: 12 April 2022

DOI: 10.1111/bjir.12679

BJIR An International Journal of Employment Relations LSE

ORIGINAL ARTICLE

Uncovered workers in plants covered by collective bargaining: Who are they and how do they fare?

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Abstract

In Germany, employers used to pay union members and non-members in a plant the same union wage in order to prevent workers from joining unions. Using recent administrative data, we investigate which workers in firms covered by collective bargaining agreements still individually benefit from these union agreements, which workers are not covered anymore and what this means for their wages. We show that about 9 per cent of workers in plants with collective agreements do not enjoy individual coverage (and thus the union wage) anymore. Econometric analyses with unconditional quantile regressions and firm-fixed-effects estimations demonstrate that not being individually covered by a collective agreement has serious wage implications for most workers. Low-wage non-union workers and those at low hierarchy levels particularly suffer since employers abstain from extending union wages to them in order to pay lower wages. This jeopardizes unions' goal of protecting all disadvantaged workers.

1 | INTRODUCTION

In recent decades, unionization has been on the decline worldwide, and collective bargaining coverage has fallen in many countries, including Germany (OECD, 2019; Schnabel, 2020; Visser, 2019). What is more, in Germany, fewer and fewer employers seem to extend the terms of the collective agreements they negotiated with unions to non-union members (which was first noted by Fitzenberger et al., 2013 but has been largely neglected in public discussions). In the past, it was a long-standing employer policy to treat union members and non-members in the same plant equally in order to prevent workers from joining unions. Abandoning this policy (plus the ongoing reduction in union membership) would imply that the effective coverage of workers by collective agreements is on the retreat, and that this retreat is even more pronounced than usually assumed. In consequence, the German system of collective bargaining may be less comprehensive, the protection of workers via collective agreements weaker and inequality between different groups of workers higher.

In addressing these topics, it is a major problem that we do not know how many and which workers currently still benefit from being covered by collective agreements – either directly by being union members who are entitled to receive the union wage or indirectly by extension of the union wage to non-union members in a plant. It is also unknown how (non-union) workers in firms covered by a collective agreement are affected if their employer decides not to extend the terms of the collective agreement to them. More specifically, it would be interesting to see what this (non-)coverage implies in terms of wages. When investigating this hitherto neglected aspect, our main focus will not be comparing the wages of similar individuals in plants that are covered or not covered by union agreements – a question which has been analysed before in the literature. We rather prefer to look at differences in (non-)coverage within a plant and analyze the resulting heterogeneity among various groups of workers.

Briefly screening the extant literature for Germany, we see that the extent of bargaining coverage as well as its fall over time in the private sector has been documented in various studies (e.g. Addison et al., 2017; Ellguth & Kohaut, 2021; Oberfichtner & Schnabel, 2019). Usually, such studies use survey data from the IAB Establishment Panel and they report the percentage of workers covered by collective bargaining under the assumption that all workers in plants bound by collective agreements receive the union wage (and employers do not differentiate between unionized and non-unionized workers). In contrast, using administrative data from the 2001 wave of the German Structure of Earnings Survey, Fitzenberger et al. (2013) show that many plants in Germany that are bound by collective agreements do not pay all their workers according to the wage laid down in the collective agreement. The authors consequently distinguish between bargaining coverage at the firm level and the individual level, and this distinction (and a more recent, expanded version of this dataset) will also be at the heart of our subsequent analysis.

Concerning the wage effects of bargaining coverage, there is some empirical evidence that workers receive higher wages in plants covered by collective bargaining, ceteris paribus, with estimates of the mean wage premium ranging from 2 per cent to 8 per cent and that this connection seems to reflect rent-sharing (e.g. Addison et al., 2010; Gürtzgen, 2009; Hirsch & Müller, 2020). Fitzenberger et al. (2013) find that a higher share of employees in a plant covered by a collective agreement is associated with higher wages, but – holding coverage at the plant-level constant – individual coverage is associated with lower wages (and less wage dispersion). Their cross-sectional study, however, is restricted to the year 2001, to West Germany, and to prime-age male employees working full-time hours in jobs without managerial duties. Hence, it does not

fully elaborate on the heterogeneity of groups of workers in terms of individual coverage and wage effects.

Against this background, the present study investigates which workers still benefit from collective agreements, which workers are not covered anymore and what this means for their wages. Using a recent and representative administrative data set and applying unconditional quantile regressions and firm-fixed-effects estimations, we contribute to the literature by addressing the following research questions:

1. How large is the share of workers in plants covered by collective bargaining who do not enjoy effective individual coverage anymore? And who are the workers who are not individually covered?
2. What are the wage implications of not being individually covered (at the mean and across the wage distribution)? And do they differ for various types of workers?
3. Do unions still achieve their goal of protecting the most disadvantaged workers, such as low-skilled and low-paid workers (e.g. Blau & Kahn, 1996)?

The paper is organized as follows: Section 2 sketches the institutional background of industrial relations and bargaining coverage in Germany and describes our rich data. Section 3 presents some descriptive evidence indicating that a substantial share of workers in plants covered by a collective agreement do not enjoy effective individual coverage (and thus not the union wage). Individual non-coverage is found to be more prevalent among men, managers and workers in the bottom and the top quarter of the wage distribution. Empirical evidence how individual (non-)coverage by collective agreements relates to workers' wages is presented in Section 4. The results of our econometric analyses with unconditional quantile regressions and firm-fixed-effects estimations demonstrate that not being individually covered by a collective agreement has serious wage implications for most workers. Low-wage non-union workers and those at low hierarchy levels particularly suffer since employers abstain from extending union wages to them, in such a way jeopardizing unions' goal of protecting all disadvantaged workers. Section 5 concludes with a discussion why non-union workers do not react to being individually uncovered by simply joining unions.

2 | INSTITUTIONAL BACKGROUND AND DATA

In Germany, the constitutionally protected principle of bargaining autonomy gives organizations of employers and employees the right to regulate wages and working conditions without state interference. Unions and employers negotiate regional or nationwide collective agreements that are legally binding and may be set up either as multi-employer agreements at industry level or as single-employer agreements at firm level. Firms may decide to be covered by these agreements, but they can also abstain from collective bargaining with unions and negotiate wages individually with their workers. If firms are bound by (single- or multi-employer) collective agreements, they cannot undercut, but only improve upon the minimum terms and conditions laid down in these agreements, through voluntary premiums, such as higher wages or more holidays. The concrete implementation and monitoring of collective agreements is often relegated to management and works councils. The latter are worker representatives that a plant's workforce may elect and that have substantial consultation and co-determination rights – albeit not concerning wage setting

(for details on the German system of industrial relations and wage setting, see Gartner et al., 2013 or Keller & Kirsch, 2021).

Collective bargaining agreements regulate wages, working hours and working conditions for all blue-collar workers and for most white-collar workers up to a certain hierarchy level, typically lower management, whereas for higher hierarchy levels contracts are negotiated individually between the employee and the employer. The wages and working conditions agreed in collective agreements apply only to the firms bound by the agreements (either directly or via membership in an employers' association) and to those of their workers who are members of the unions that signed the agreements. Non-union workers in a plant are not entitled to be paid the union wage laid down in the collective agreement.[1] But employers are free to extend the agreed wages to workers who are not union members, in such a way reducing these workers' incentive to join the union in order to receive the union wage.[2] For many years, most employers have adopted such a strategy that intends to keep unionization low, so that the bargaining coverage of a firm was assumed to be equivalent to the bargaining coverage of its workers.

In fact, the most frequently used indicator of the bargaining coverage rate in Germany, which is based on an annual survey of about 16,000 plants in the IAB Establishment Panel (for details, see Ellguth & Kohaut, 2021), follows this reasoning. It asks plants whether they are covered by a multi- or single-employer collective agreement and then reports the percentage of workers covered in the economy or in a sector under the premise that all workers in plants bound by collective agreements receive the union wage (assuming that firms do not differentiate between union members and non-unionized employees).

The picture differs if firms decide to pay the wage laid down in a collective agreement only to union members who are directly entitled to this wage, but do not extend this wage to non-union members.[3] This increasingly seems to be the case in Germany. Fitzenberger et al. (2013) show that among those plants in Germany that are bound by collective agreements, the large majority does not pay all their workers according to the wage laid down in the collective agreement. This insight is based on the German Structure of Earnings Survey (SES henceforth) for the year 2001, an administrative data set that allows a finer distinction in terms of worker coverage and that we also use in our empirical analysis.

We make use of the two latest surveys of the SES for the years 2014 and 2018, which are provided as scientific use files by the Federal Statistical Agency (*Statistisches Bundesamt*) of Germany (for details, see Federal Statistical Agency, 2016, 2020). The SES 2014 and SES 2018 are representative surveys of all German firms with at least one worker, and each survey contains information on about 70,000 firms and one million workers. The data quality of these rich employer–employee data is high because most observations originate from firms' personnel records and because firms are obliged by law to answer the survey correctly, so that the SES differs from the IAB Establishment Panel in terms of its mandatory nature. It also differs from the latter in that it surveys all plants employing at least one worker and not just those plants with at least one worker subject to social security contributions. The survey's wider population, in turn, means that the SES also contains, for instance, small owner-led firms with only marginally employed among their workforce, such as restaurants, shops and so on, which are absent from the IAB Establishment Panel.

Crucial for our purpose, the SES not only asks whether a plant is bound by a single- or multi-employer collective agreement, but covered plants also have to report for a random sample of their workers whether these are paid according to a collective agreement.[4] Consequently, the information from the SES allows us to identify uncovered workers in covered plants and thus to observe the effective individual coverage of workers by collective agreements. That said, two drawbacks of our data are that the surveys are repeated cross sections rather than panel data and that they

TABLE 1 Worker coverage rates

	Year		
	2014	2018	
	coverage rate (%)		Δ pp
Worker works in a covered plant			
Overall	42.85	37.91	−4.94
Multi-employer agreement	33.85	31.48	−2.37
Single-employer agreement	9.00	6.43	−2.57
Worker is individually covered by a collective agreement			
Overall	39.37	34.37	−5.00
Multi-employer agreement	30.93	28.38	−2.55
Single-employer agreement	8.44	5.99	−2.45
Share of uncovered workers among workers in covered plants			
Overall	8.12	9.34	1.22
Multi-employer agreement	8.63	9.85	1.22
Single-employer agreement	6.22	6.84	0.62

Note: SES 2014 and 2018. Weighted using sample weights.

do not include information on the existence of works councils which form the second backbone of the German model of industrial relations (Oberfichtner & Schnabel, 2019).

Apart from the information about collective agreement coverage, the SES data include a wide set of worker and plant characteristics. Worker characteristics comprise, *inter alia*, information on workers' earnings, sex, age, job tenure, working hours, educational attainment as well as on hierarchy levels, temporary (as opposed to permanent) contracts and occupations.[5] The SES data thus differ from other administrative data for Germany, in particular the linked employer–employee data provided by the IAB, in that they contain detailed information on working hours and thus accurate hourly wages, and in that the included earnings information is not subject to censoring, thereby permitting us to analyse top earners' wages.[6] Plant characteristics include information on firm size, workplace size, industry, location in either West or East Germany and coverage by collective wage agreements as detailed above. We use these data to build up a sample of workers aged 18–65 years employed in the private sector, excluding apprentices, marginally employed, partial retirees and temporary agency workers.

3 | DESCRIPTIVE EVIDENCE

Using the SES data, Table 1 provides various coverage rates of collective agreements for the years 2014 and 2018, where we weight observations for individual workers using the SES sample weights. The first coverage rate reports the percentage of workers employed by a plant that is bound by a collective agreement and thus implicitly assumes that all workers in a covered plant are also covered at individual level. In 2014, 43 per cent of workers hold jobs at a covered plant, where 34 per cent of workers are employed by a plant covered by a multi-employer agreement and 9 per cent by a plant covered by a single-employer agreement. Four years later in 2018, only 38 per cent of workers hold jobs at covered plants, which amounts to a fall in the coverage rate by 5 percentage

points. Furthermore, in 2018, 31 per cent or 6 per cent of workers, respectively, are employed by a plant covered by a multi-employer or single-employer agreement.

Comparing these numbers to numbers obtained from the IAB Establishment Panel, which also allows to calculate the share of workers employed by covered plants, we find that coverage rates from the IAB data are generally higher (but the downward trend is quite similar). In 2014, 58 per cent of workers in the IAB data work in plants covered by collective agreements, and 54 per cent of workers do so in 2018 (Ellguth & Kohaut, 2015, 2019). This discrepancy, however, is hardly surprising because the population of the IAB Establishment Panel is restricted to plants with at least one worker subject to social security contributions and thus misses all those small plants unlikely to be covered by collective agreements that only employ workers who are not subject to social security contributions, for example owner-led plants with only marginally employed workers.

The second coverage rate in Table 1 reports the percentage of workers who are individually covered by a collective agreement, that is workers who work at a covered plant and receive the union wage. In 2014, 39 per cent of workers are covered by collective agreements and this number falls by 5 percentage points to 34 per cent 4 years later. These numbers are lower than the percentages of workers employed by covered plants and thus make clear that a non-negligible number of workers are indeed uncovered by collective agreements despite working for a covered plant. In other words, we have clear evidence that employers do not extend union wages to all non-union members and that the prevalence of such exemptions is non-trivial in magnitude.

Specifically, in 2014, 8 per cent of workers employed by a covered plant are uncovered, and this number even rises somewhat to 9 per cent in 2018 (Table 1). What is more, we see that the prevalence of exemptions is smaller for single-employer than for multi-employer collective agreements, which suggests that single-employer agreements are more often extended to non-unionized workers (though we lack information on individual union membership to substantiate this point because we do not know whether unionization rates are different across plant with single- and multi-employer collective agreements). That exemptions are larger for multi- than for single-employer agreements seems plausible given that the latter are tailor-made for the specific employer at hand.

Next, Table 2 shows for the most recent SES 2018 survey coverage rates across different groups of workers. Both the percentage of workers employed by a covered plant and the prevalence of workers who are individually covered by a collective agreement vary substantially across these groups of workers considered, but the patterns of both are in general very similar. We thus focus on the rate of individual coverage. Individual coverage is larger in West (35 per cent) than in East Germany (29 per cent), and it varies substantially among firms of different size and among sectors. Individual coverage is substantially rising with firm size and, among sectors, it is highest in agriculture, mining, energy and water (49 per cent) and lowest in services (31 per cent).

Turning to worker characteristics, we find that individual coverage is higher for workers aged 50 or older compared to younger workers, but similar for men and women and for workers on full-time and part-time hours. We further find substantial differences in individual coverage along hierarchy levels. 43 per cent of specialists, which is the second-highest category, are individually covered followed by workers on simple tasks at the bottom of the hierarchy, where 38 per cent are individually covered. For workers on the other three hierarchy levels, the individual coverage rate ranges from 30 per cent to 35 per cent. Moreover, individual coverage is much higher in the upper half of the wage distribution (46–47 per cent in the two top quarters of the wage distribution) than in the bottom half (15 per cent in the lowest and 30 per cent in the second quarter of the distribution). If individual coverage leads to wage gains, we expect to see more covered workers in the upper part of the wage distribution, in line with these patterns.

TABLE 2 Worker coverage for subgroups in 2018

	Worker works in a covered plant (%)	Worker is individually covered by a collective agreement (%)	% of uncovered workers among workers in covered plants
West	38.91	35.21	9.51
East	31.45	28.89	8.14
Agriculture, mining, energy and water	52.76	49.23	6.69
Construction	44.12	39.02	11.56
Manufacturing	45.08	41.08	8.87
Services	34.69	31.38	9.54
Firm size			
1–49	16.33	14.84	9.12
50–250	30.98	27.88	10.01
250 and more	64.75	58.80	9.19
Men	37.57	33.50	10.83
Women	38.30	35.37	7.65
Full-time	38.17	34.23	10.32
Part-time	37.38	34.65	7.30
Age			
18–29	34.09	31.28	8.24
30–49	36.34	32.89	9.49
50 and older	41.46	37.50	9.55
Hierarchy level			
Managerial duties	45.89	34.72	24.34
Specialist	47.92	42.59	11.12
Experienced worker	34.30	32.24	6.01
No decision making	32.32	30.08	6.93
Simple tasks	41.31	38.31	7.26
Wage quartiles			
Wage < Q1	16.88	14.74	12.68
Q1 < Wage < Median	32.18	29.69	7.74
Median < Wage < Q3	48.45	46.24	4.56
Wage > Q3	54.11	46.78	13.55

Note: SES 2018. Weighted using sample weights.

Our main interest is analyzing the non-extension of collective agreements reported in the last column of Table 2. Although there are some differences across subgroups in the number of workers who are uncovered by collective agreements despite working for covered plants, on which we will comment in a moment, the general impression is that the non-extension of collective agreements is pervasive. For only few groups of workers, we find substantial deviations from the average share of uncovered workers in covered plants of 9 per cent.

Turning to the differences across groups of workers, we find little such differences among East and West Germany, among firms of different size and among workers of different age. However, there exist some non-trivial differences across some groups. Among sectors, exemptions are most often found in construction (12 per cent) and least often among agriculture, mining, energy and water (7 per cent). Men (11 per cent) are more often uncovered by collective agreements despite working for a covered plant than women (8 per cent) and full-time workers (10 per cent) more often than part-time workers (7 per cent); in other words, these groups of workers are more often exempt from collective agreements. Moreover, we see that workers at higher hierarchy levels are much more often exempt than workers at lower hierarchy levels. Whereas 24 per cent of workers with managerial duties and 11 per cent of specialists are exempt, the same holds true for only 6–7 per cent of experienced workers, workers with no decision making and workers with simple tasks. The high share of workers with managerial duties who are not covered by collective agreements is not surprising given the fact (mentioned above) that for higher hierarchy levels, contracts are often negotiated individually between the employee and the employer rather than collectively with the union.

Finally, we see clear differences in exemption rates along the wage distribution. Whereas 13 per cent of workers in the bottom quarter of the wage distribution and 14 per cent of workers in the top quarter are exempt from collective agreements, just 5 per cent of workers in the second and 8 per cent of workers in the third quarter are uncovered by collective agreements despite working for a covered plant. This latter finding not only documents that low-wage and high-wage workers are more often exempt from collective agreements, but it also suggests that employers' decision not to extend union wages is specifically targeted at these two groups. It is tempting to suspect that firms do not extend the collective agreement to low-wage workers to pay lower wages to these workers, which would, in turn, mean that particularly vulnerable low-wage workers would suffer more from not getting the union wage. On the other hand, employers often exempt high-wage workers from collective agreements to negotiate their pay individually, which may result in even higher wages to these workers than to covered workers. We will investigate these possibilities in more detail in the following section.

Answering our first research question, the descriptive evidence presented here makes clear that a substantial share of about 9 per cent of workers in plants covered by a collective agreement do not enjoy effective individual coverage (and thus not the union wage). Individual non-coverage is more pronounced among some groups of workers, such as men, managers and workers, in the bottom and the top quarter of the wage distribution.

4 | WAGE EFFECTS

We now turn to how individual coverage by collective agreements relates to workers' wages. To that end, we run several wage regressions on the most recent 2018 SES survey.[7] Specifically, we regress the log hourly wage In w_{ij} of worker i employed by plant j on a dummy indicating individual coverage of the worker $workercovered_i$, a dummy indicating a plant covered by a collective agreement $plantcovered_j$ and a set of worker and plant controls $\mathbf{x}_i$ and $\mathbf{z}_j$, respectively. Hence, our baseline regression model reads:

$$\ln w_{ij} = \beta_0 + \beta_1 workercovered_i + \beta_2 plantcovered_j + \mathbf{x}_i'\gamma + \mathbf{z}_j'\delta + u_{ij} \quad (1)$$

where u_{ij} denotes the regression model's error term. Note that by construction the dummy $workercovered_i$ will only be one if the individual worker is covered by a collective agreement

TABLE 3 OLS, fixed-effects and RIF regressions (SES 2018)

OLS regression for the mean and RIF regressions for different quantiles of workers' log wage						
	Mean	**p10**	**p25**	**p50**	**p75**	**p90**
Worker covered	−0.00825	0.0783	0.128	0.114	−0.0416	−0.376
	(0.00634)	(0.00624)	(0.00725)	(0.00705)	(0.0109)	(0.0216)
Plant covered	0.0862	0.00964	0.0413	0.0202	0.0895	0.312
	(0.00674)	(0.00654)	(0.00752)	(0.00721)	(0.0110)	(0.0221)
Fixed-effects OLS regression for the mean and RIF regressions for different quantiles of workers' log wage						
	Mean	**p10**	**p25**	**p50**	**p75**	**p90**
Worker covered	−0.0544	0.0643	0.0936	0.109	−0.0432	−0.557
	(0.00609)	(0.00590)	(0.00639)	(0.00707)	(0.0128)	(0.0254)

Note: SES 2018. Standard errors clustered at plant level in parentheses. Further controls included in the regressions are the worker's age (linearly and squared), tenure (linearly and squared); dummies for the worker's education, sex, two-digit occupation, hierarchy level, for working on full-time hours and on a temporary contract; and, in the regressions without plant fixed effects, dummies for firm size, plant size and plant location in East Germany.

and also works for a covered plant meaning that $plantcovered_j$ is one, too. Hence, β_2 informs us on the wage consequences of plant coverage, that is the difference of wages of uncovered workers at covered and uncovered plants, whereas β_1 gives the wage consequences of individual coverage in covered plants.[8]

To estimate how individual coverage relates to wages along the wage distribution, we estimate Equation (1) for the mean of the wage distribution by OLS and we run unconditional quantile regressions for various quantiles of the wage distribution using the recentred influence function (RIF) approach (Firpo et al., 2009).[9] In all these regressions, β_1 is identified from both between-plant and within-plant variation in wages that is left after controlling for worker and plant characteristics.

Since our focus is on the wage consequences of individual coverage by collective agreements, an alternative approach is to use within-plant variation in wages only, that is to just compare covered and uncovered workers within plants that are covered by collective agreements (remember that in uncovered plants, $workercovered_i$ is zero by construction). For that purpose, we also run fixed-effects regressions:

$$\ln w_{ij} = \alpha_j + \tilde{\beta}_1 workercovered_i + \mathbf{x}_i'\tilde{\gamma} + \varepsilon_{ij} \tag{2}$$

where α_j denotes the fixed effect belonging to plant j, which thus both absorbs the dummy for covered plants $plantcovered_j$ and all other plant controls $\mathbf{z}_j$, and ϵ_{ij} is the error term. The big advantage of regression model (2) over model (1) is that comparing workers within plants means controlling for all plant observables and unobservables, in particular for the existence of works councils, which we do not observe in our data and which has been found to matter significantly for wages (e.g. Addison et al., 2010; Hirsch & Müller, 2020). In the fixed-effects regression (2), $\tilde{\beta}_1$ is identified solely from wage differences between covered and uncovered workers who are employed by the same plant and thus informs us on the wage advantage of covered over uncovered workers within covered plants. Again, we estimate Equation (2) for the mean of the wage distribution by OLS and for various quantiles of the unconditional wage distribution in RIF regressions.

Table 3 reports the baseline estimates of regression models (1) and (2) for the mean of the wage distribution and beyond. In terms of worker characteristics, the models control for workers'

educational attainment, sex, age (linearly and squared), job tenure (linearly and squared), two-digit occupation as well as for the hierarchy level, a temporary contract and working full-time. In terms of plant characteristics, the models without plant fixed effects control for firm size, plant size, two-digit industry and plant location in East Germany (which will be otherwise absorbed by the fixed effect).

In the regressions without plant fixed effects in the upper panel of Table 3, we see that plant coverage by collective agreements is associated with higher wages at the mean and particularly in the upper part of the wage distribution, *ceteris paribus*.[10] The OLS estimate of the coefficient of plant coverage of 0.086 implies that a 10 percentage points larger rate of covered plants is associated with an increase in the mean wage by about 0.9 per cent, which is statistically significant at the 1 per cent level. The associated increase is of similar magnitude for the third quartile and amounts to even 3.1 per cent for the ninth decile, whereas it is much smaller in magnitude for lower quantiles. Although the positive correlation between wages and plant coverage could reflect that plant coverage per se is driving up wages, it is no less consistent with the view that covered plants perform better and, for this reason, pay higher wages.

Turning to the wage consequences of workers' individual coverage by collective agreements in covered plants, we see no significant association (neither in economic nor in statistical terms) of individual coverage with the mean wage. Yet, this finding obscures divergent impacts of individual coverage on the lower and the upper part of the wage distribution that together compress the wage distribution without altering its centre. A 10 percentage points larger rate of individual coverage by collective agreements is associated with a statically significant rise in the first decile, the first quartile and the median of wages in the range of 0.8–1.3 per cent. This finding suggests that employers abstain from extending union wages to low-wage non-union workers in order to pay lower wages to this group.[11] Yet, these results for the lower half of the wage distribution contrast with what we find for high-wage workers at the top of the distribution. A 10 percentage points larger rate of individual coverage is associated with significant drop in the third quartile by 0.4 per cent and a significant drop in the ninth decile by even 3.8 per cent. These findings suggest that for uncovered high-wage workers, union wages are considerably lower than the wages paid to them outside the collective agreement, in line with our previous reasoning.

Turning to the lower panel of Table 3 that shows fixed-effects wage regressions, we see that the wage consequences of individual coverage in covered plants change little when we rest identification exclusively on the comparison of wages of covered and uncovered workers within covered plants. The only exception are workers at the very top of the wage distribution. A 10 percentage points larger individual coverage rate is now associated with a significant drop in the ninth decile by 5.6 per cent (compared to 3.8 per cent in the model without the fixed effects). This more pronounced wage compression of individual coverage at the top of the wage distribution, in turn, means that such an increase in individual coverage is now associated with a slightly lower mean wage by 0.5 per cent. Figure 1 clearly shows that individual coverage is accompanied by higher wages up to the seventh decile of the wage distribution, whereas it is associated with lower wages for top earners.

Next, we run separate fixed-effects OLS and RIF regressions for West and East Germany, for men and women, and for workers at different hierarchy levels. Table 4 shows the core estimates for the impact of workers' individual coverage by collective agreements in covered plants. It corroborates the general patterns found in Table 3 for most groups, but it also points at some rather suggestive differences across groups. To start with, we find little differences between West and East Germany and between men and women. For all these groups, an increase in individual coverage is accompanied by higher wages in the lower half of the wage distribution and by smaller

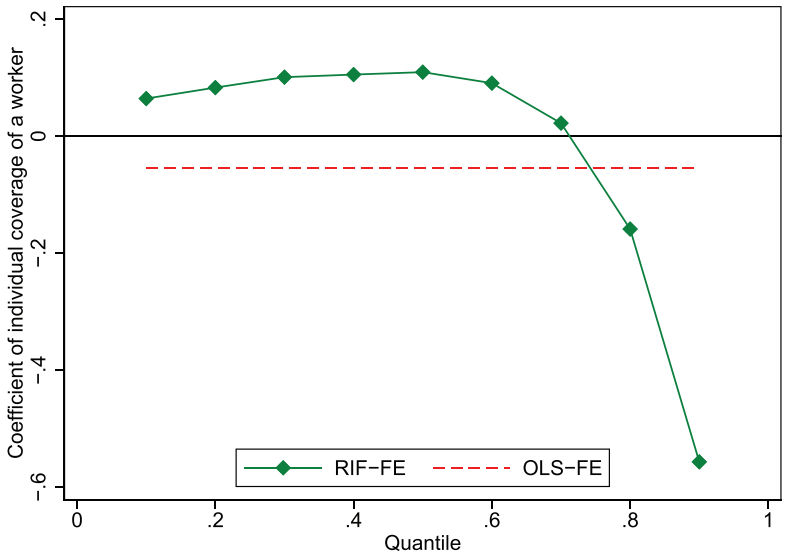

FIGURE 1 Estimated coefficient of individual coverage of a worker by a collective agreement in a covered plant from fixed-effects OLS and RIF regressions [Colour figure can be viewed at wileyonlinelibrary.com]

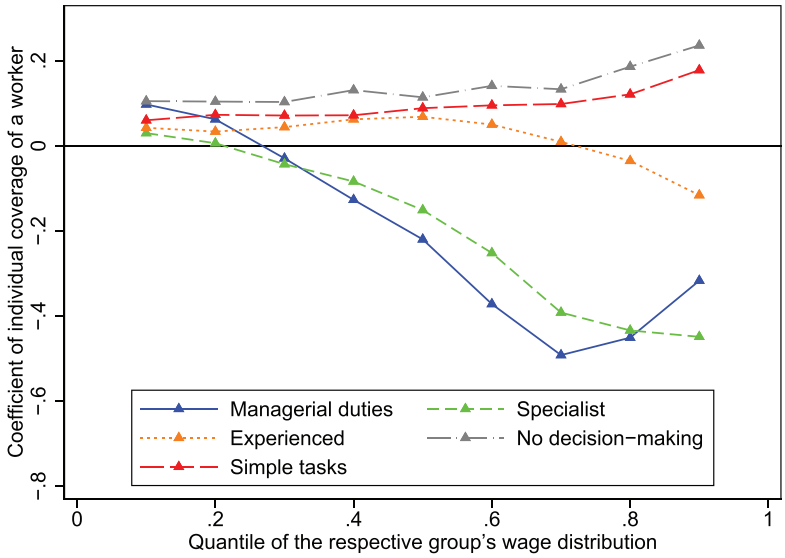

FIGURE 2 Estimated coefficient of individual coverage of a worker by a collective agreement in a covered plant from fixed-effects RIF regressions by hierarchy level (SES 2018) [Colour figure can be viewed at wileyonlinelibrary.com]

wages at the top of the wage distribution, so that individual coverage significantly compresses the unconditional wage distribution. The only difference across groups is that the negative impact of individual coverage on wages in the upper part of the wage distribution occurs at lower quantiles for West German compared to East German workers and for men compared to women. This finding may reflect that we observe fewer top earners in East Germany and among women who for this reason are exempt from collective agreements (i.e. are individually uncovered despite working for a covered plant).

Turning to workers at different hierarchy levels, we find clear differences in the wage consequences of individual coverage (see also Figure 2). For workers with simple tasks and workers without decision making, higher individual coverage lifts the entire wage distribution and even more so the distribution's upper part, so that an increase in individual coverage not only improves wage outcomes generally but also widens the wage distribution of these low-hierarchy workers. In other words, uncovered low-hierarchy workers in covered plants lose substantially compared to their covered counterparts and high earners among low-hierarchy workers even more so. This implies that joining a union in order to obtain the union wage is particularly attractive to higher-wage low-hierarchy workers.[12]

TABLE 4 Fixed-effects and RIF regressions for subgroups (SES 2018)

Fixed-effects OLS regression for the mean and RIF regressions for different quantiles of workers' log wage (estimates of the coefficient of worker covered)						
	Mean	**p10**	**p25**	**p50**	**p75**	**p90**
West	−0.0570	0.0706	0.0924	0.100	−0.0786	−0.556
	(0.00653)	(0.00754)	(0.00684)	(0.00775)	(0.0139)	(0.0267)
East	−0.0372	0.0688	0.0701	0.126	0.0860	−0.269
	(0.0159)	(0.0117)	(0.0144)	(0.0169)	(0.0280)	(0.0518)
Men	−0.0766	0.0663	0.0898	0.0927	−0.144	−0.630
	(0.00675)	(0.00739)	(0.00728)	(0.00979)	(0.0160)	(0.0310)
Women	−0.0185	0.0616	0.0734	0.100	0.0571	−0.320
	(0.00888)	(0.00980)	(0.0115)	(0.00921)	(0.0149)	(0.0349)
Hierarchy level						
Managerial duties	−0.192	0.0973	0.0212	−0.220	−0.537	−0.317
	(0.0117)	(0.0184)	(0.0178)	(0.0238)	(0.0362)	(0.0431)
Specialists	−0.195	0.0299	−0.0159	−0.151	−0.441	−0.449
	(0.00830)	(0.0127)	(0.0129)	(0.0157)	(0.0224)	(0.0356)
Experienced	0.0128	0.0424	0.0442	0.0683	−0.0124	−0.116
	(0.00990)	(0.0139)	(0.0151)	(0.0151)	(0.0213)	(0.0265)
No decision making	0.166	0.105	0.101	0.114	0.166	0.236
	(0.0588)	(0.0392)	(0.0385)	(0.0471)	(0.0554)	(0.118)
Simple tasks	0.118	0.0600	0.0613	0.0885	0.120	0.178
	(0.0337)	(0.0171)	(0.0271)	(0.0393)	(0.0582)	(0.110)

Note: SES 2018. Standard errors clustered at plant level in parentheses. Further controls included in the regressions are the worker's age (linearly and squared), tenure (linearly and squared); dummies for the worker's education, sex, two-digit occupation, hierarchy level, for working on full-time hours and on a temporary contract; and, in the regressions without plant fixed effects, dummies for firm size, plant size and plant location in East Germany.

These findings for low-hierarchy workers contrast with workers at higher hierarchy levels. For experienced workers in the middle of the hierarchy, the wage consequences of individual coverage look quite similar to what we found for all workers in Table 3, that is individual coverage is associated with higher wage quantiles up to the median and a drop in the wage quantiles at the top. Finally, for specialists and workers with managerial duties at the top of the hierarchy, the negative impact of individual coverage for wages occurs at considerably lower quantiles. These contrasting wage impacts of individual coverage for workers at different hierarchy levels suggest that employers abstain from extending the union wage to low- and high-hierarchy workers for different reasons: to pay even lower wages for low-wage workers at the bottom of the hierarchy, who would thus gain from individual coverage; and to pay even higher wages to high-wage workers at the top of the hierarchy, who would thus receive lower wages when individually covered and, in turn, gain from being exempt from the collective agreement.

To check the robustness of our findings, we now turn to the SES 2014 survey and run our preferred fixed-effects wage regressions on this sample, too. Table 5 reports fixed-effects OLS and RIF regressions akin to those from Tables 3 and 4 for the 2018 SES survey. Comparing the estimates for all workers and the separate estimates for East and West Germany as well as for men and women, we only find little differences across the SES 2014 and SES 2018 surveys. Turning to the separate

TABLE 5 Fixed-effects and RIF regressions (SES 2014)

Fixed-effects OLS regression for the mean and RIF regressions for different quantiles of workers' log wage (estimates of the coefficient of worker covered)						
	Mean	**p10**	**p25**	**p50**	**p75**	**p90**
All workers	−0.0595	0.0878	0.102	0.107	−0.0242	−0.622
	(0.00693)	(0.00658)	(0.00655)	(0.00663)	(0.0133)	(0.0341)
West	−0.0676	0.0817	0.0991	0.0902	−0.0593	−0.664
	(0.00752)	(0.00629)	(0.00679)	(0.00720)	(0.0157)	(0.0333)
East	0.00129	0.115	0.0837	0.126	0.114	−0.153
	(0.0140)	(0.0163)	(0.0137)	(0.0182)	(0.0275)	(0.0399)
Men	−0.0930	0.0935	0.0928	0.0869	−0.125	−0.787
	(0.00766)	(0.00817)	(0.00666)	(0.00909)	(0.0177)	(0.0322)
Women	0.0016	0.0882	0.0735	0.111	0.0577	−0.197
	(0.0108)	(0.0112)	(0.0103)	(0.0101)	(0.0146)	(0.0384)
Hierarchy level						
Managerial duties	−0.224	0.0415	−0.0152	−0.243	−0.527	−0.340
	(0.0115)	(0.0127)	(0.0257)	(0.0308)	(0.0444)	(0.0421)
Specialists	−0.215	0.0525	−0.00330	−0.0992	−0.445	−0.674
	(0.00986)	(0.0145)	(0.0122)	(0.0180)	(0.0293)	(0.0572)
Experienced	−0.0129	0.0241	0.0395	0.0442	−0.0501	−0.185
	(0.0100)	(0.0136)	(0.0125)	(0.0118)	(0.0182)	(0.0315)
No decision making	0.237	0.224	0.172	0.213	0.174	0.257
	(0.0463)	(0.0509)	(0.0287)	(0.0376)	(0.0412)	(0.105)
Simple tasks	0.262	0.541	0.232	0.147	0.149	0.108
	(0.0474)	(0.0865)	(0.0383)	(0.0312)	(0.0490)	(0.0761)

Note: SES 2014. Standard errors clustered at plant level in parentheses. Further controls included in the regressions are the worker's age (linearly and squared), tenure (linearly and squared); dummies for the worker's education, sex, two-digit occupation, hierarchy level, for working on full-time hours and on a temporary contract; and, in the regressions without plant fixed effects, dummies for firm size, plant size and plant location in East Germany.

estimates by workers' hierarchy level, however, we see some changes in the impact of individual coverage for the two lowest hierarchy levels. For workers with simple tasks and for workers without decision making, individual coverage has a much bigger positive impact on the lower wage quantiles (up to the median) in the SES 2014 than in the SES 2018 survey (see also Figure 3). One likely explanation for this difference is that the introduction of the statutory minimum wage in Germany in 2015 lifted the wages of uncovered low earners among the low-hierarchy workers to such an extent that for this group, individual coverage is no longer accompanied by substantial wage gains in 2018, thereby also weakening the incentives for this group of workers to join a union. That said, this difference in the estimates for low-wage, low-hierarchy workers does not change any of our insights from the SES 2018 survey.

In terms of our second research question, the econometric analyses have shown that not being individually covered by a collective agreement has substantial wage implications for most workers. In particular, it is low-wage non-union workers who suffer since employers abstain from extending union wages to them, probably to be able to pay lower wages to this group. In terms of hierarchy level, we find corresponding evidence for workers who perform simple tasks and who

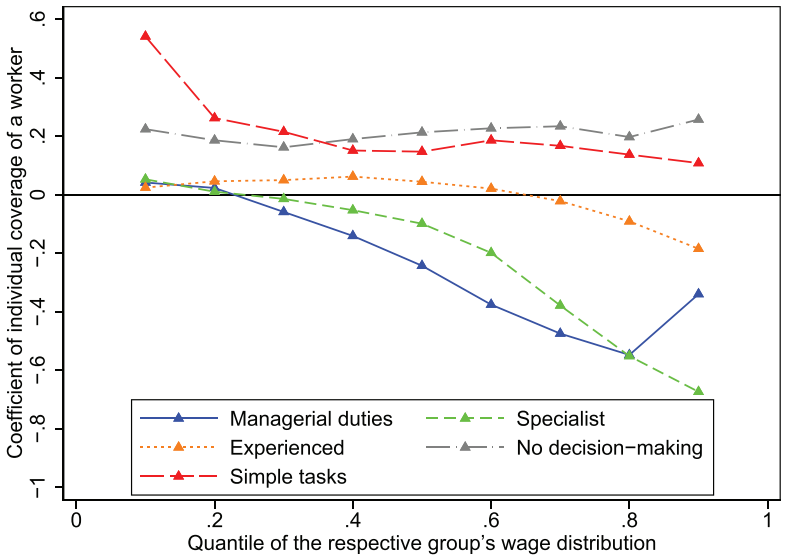

FIGURE 3 Estimated coefficient of individual coverage of a worker by a collective agreement in a covered plant from fixed-effects RIF regressions by hierarchy level (SES 2014) [Colour figure can be viewed at wileyonlinelibrary.com]

are not involved in decision making. With respect to our third research question, these findings imply that the German unions' goal of protecting the most disadvantaged workers (not only union members) seems to be jeopardized by employers not extending the wages and working conditions laid down in collective agreements to non-union workers.

5 | CONCLUSIONS

Using representative administrative data for Germany, this study has investigated which workers in firms covered by collective bargaining agreements still individually benefit from these agreements, which workers are not covered anymore and what this means for their wages. Substantiating and updating an early insight by Fitzenberger et al. (2013), we show that many plants bound by collective agreements do not pay all their workers according to the wage laid down in these agreements, so that the effective individual coverage of workers by collective agreements is much lower than usually assumed. In 2018, a substantial share of about 9 per cent of workers in plants covered by a collective agreement did not enjoy individual coverage (and thus the union wage) anymore. Individual non-coverage concentrates among men, managers and workers in the bottom and the top quarter of the wage distribution.

Our econometric analyses with unconditional quantile regressions and firm-fixed-effects estimations demonstrate that not being individually covered by a collective agreement has serious wage implications for most workers. Low-wage non-union workers particularly suffer since employers abstain from extending union wages to them, arguably to be able to pay lower wages. In terms of hierarchy level, we find corresponding evidence for workers who perform simple tasks and who are not involved in decision making. Although unions in Germany still pursue their goal of protecting the most disadvantaged workers, such as low-skilled and low-paid workers, and also achieve this goal for their members (because collective agreements directly apply to members if they work for an employer covered by such an agreement), employers increasingly seem to counteract by not extending the wages and working conditions laid down in collective agreements to non-union workers. This behaviour may be a reaction to long-standing employer complaints that union wages are too high, in particular for less qualified workers (discussed, e.g., by Schnabel, 2003). It also suggests that some employers seem to have given up their traditional policy of treating union members and non-members equally to prevent workers from joining unions.

Given this unequal treatment, it is an open question why non-union workers do not react to the fact (or threat) of being individually uncovered by simply joining unions. Although union membership dues are about 1 per cent of gross wages (Goerke & Pannenberg, 2011), these additional costs are in many cases lower than the earnings foregone when not receiving the union wage. Of course, some workers may still be free-riding successfully if their employers do not differentiate between unionized and non-unionized workers and pay the same wage to all of them. But we have shown that in particularly many of the most disadvantaged non-union workers would get higher wages if they became union members. Nevertheless, like in many other countries, union membership and density hsteadily falling in Germany, and the share of low-skilled workers among union members is lower than their share in employment (Biebeler & Lesch, 2015). Union recruiting probably should focus more on these disadvantaged workers and make clearer to them what the economic benefits from joining the union are. That said, it is not only rational choice considerations but also social, political and psychological factors that influence individuals' decision (not) to become a union member (see the survey by Schnabel, 2020).

One policy option discussed in Germany is promoting union membership by making membership dues tax-deductible to a greater extent than currently possible. To avoid unequal treatment of workers, Germany could adopt *erga omnes* clauses that automatically extend coverage by a collective agreement by applying it to all workers in a firm, not only members of the signatory union, which (*de jure* or *de facto*) is the case in many other countries (see OECD, 2019, p. 49). However, German employers generally oppose statutory bargaining extensions, which contrasts with other countries, such as the Netherlands (see the comparison of these two countries by Paster et al., 2020). Finally, unequal treatment of (low-wage) workers will also be reduced to some extent by the substantial increase in the statutory minimum wage to 12 Euros per hour, which is planned for 2022 by the new government in Germany.

A certain limitation of our analysis is that we only have cross-sectional and not panel data, so we cannot claim to have identified causal effects of individual non-coverage for affected workers. Despite this caveat, our detailed administrative data allow us to provide fresh evidence on how individual non-coverage and the resulting negative wage effects are related to personal and workplace characteristics. Once panel data are available, a promising area of further research may be analyzing which factors have played a role over time in explaining firms' decision not to extend the terms of collective agreements to all workers in a plant and how this has affected individuals' earnings and employment paths as well as overall wage inequality.

ACKNOWLEDGEMENTS

The authors would like to thank Laszlo Goerke, Susanne Kohaut, Thorsten Schank and two anonymous referees for helpful comments and suggestions. They further appreciate comments by seminar participants in Lüneburg and Nuremberg.

Open access funding enabled and organized by Projekt DEAL.

DATA AVAILABILITY STATEMENT

This study uses the German Structure of Earnings Survey (*Verdienststrukturerhebung*), waves 2014 and 2018, which are available as Scientific Use Files from the Federal Statistical Agency (*Statistisches Bundesamt*) of Germany.

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ENDNOTES

[1] This principle of 'double affiliation', that is collective agreements directly cover only employees who are members of the union signing the agreement and work in a firm member of the signatory employer association, also applies in several other countries, such as Sweden, Japan and Korea. In contrast, in many countries, there exist *erga omnes* clauses that extend the terms set in collective agreements to all employees, not restricted to the members of the signatory unions. For details, see OECD (2019, p. 49).

[2] When joining a union, workers must pay a membership fee of about 1 per cent of gross wages (Goerke and Pannenberg 2011).

[3] If employers bound by a collective agreement do not want to pay the union wage to all workers in the plant, they either have to ask workers whether they are members of the union that concluded the agreement and are thus entitled to receive the union wage or they wait for workers declaring their union status. Refusing to pay union members the union wage would be a legal offence and could be easily detected since the terms of the collective agreement become public knowledge.

[4] Specifically, in the survey's questionnaire, plants report (based on their personnel files) whether for each selected worker a multi-employer or a single-employer agreement applies or no collective agreement at all. As the data further include information on whether the plant is bound by a collective agreement or not, we can combine these two pieces of information to identify individual coverage or non-coverage of a worker employed by a covered plant.

[5] The SES 2014 and 2018 distinguish five different hierarchy levels: workers with simple tasks, workers without decision making, experienced workers, specialists and workers with managerial duties. Workers are assigned into these levels based on the occupational grouping in the collective agreement or, if no collective agreement applies, based on a grouping by the firm along the same dimensions laid down in collective agreements.

[6] The exception is a negligible number of workers with exceptionally high earnings, that is yearly earnings exceeding € 750,000, whose earnings are censored and whom we, for this reason, exclude from our analysis.

[7] We decided against pooling observations from the 2014 and 2018 SES cross sections because the large sample size of the 2018 survey alone guarantees sufficient power in estimation. Besides, our insights do not change when running the wage regressions on the 2014 SES survey instead, which we do in a later robustness check.

[8] Note that our specification does not distinguish plants covered by single-employer and plants covered by multi-employer collective agreements. In regressions that include both groups separately, we find little differences that do not change our insights. Besides, estimates for coverage by single-employer agreements are much less precise, which is hardly surprising given that multi-employer agreements are still the norm in Germany.

[9] We estimate the RIF regressions in Stata using the user-written programs by Rios-Avila (2020).

[10] As detailed in Firpo et al. (2009), RIF regressions approximate the impact of an infinitesimal change in the distribution of a regressor on the respective unconditional quantile of the outcome distribution. For dummy variables, such as the dummy for a plant covered by a collective agreement in our wage RIF regressions, a unit change would refer to a very large change, that is from no coverage of any plant to complete coverage of all plants, and consequently the impact of such a large change in the coverage rate on the outcome distribution may be badly approximated by the RIF regression. For this reason, we will all the time consider, as a thought experiment, an increase in the coverage rate by 10 percentage points, which, for example, means that the rate of plant coverage increases from its mean of 38 per cent of workers to 48 per cent of workers.

[11] Keep in mind, though, that we found mean wages and all unconditional wage quantiles to be significantly higher in covered than in uncovered plants, which means that overall, that is when summing up $\hat{\beta}_1$ and $\hat{\beta}_2$, uncovered workers in covered plants are still not worse off than their counterparts in uncovered plants. The only exception are high-wage workers at the top of the wage distribution as for the ninth decile the sum of these two is slightly negative.

[12] That low-hierarchy workers would gain most from individual coverage may arouse concerns that these workers respond by joining a union, thereby rendering individual coverage endogenous in the wage regressions. Although we cannot rule out some such endogenous responses of individual coverage, we see little evidence in our data suggesting a big role for this concern. As we saw before, low-hierarchy workers are not less often uncovered by collective agreements despite working for a covered plant than workers at higher levels. Moreover, we do not find that the rise in the exemption rate from collective agreements over time is absent for low-hierarchy workers. In short, our data do not suggest (much) endogenous responses in individual coverage.

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Second job holding in Germany — a persistent feature?

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Abstract: This paper investigates the persistence and determinants of second job holding in Germany, especially marginal second jobs, following a legislative change allowing extensive dispensation of marginal second jobs from taxes and social security contributions. I document an upward trend in second job holding driven in particular by women. Moreover I find strong evidence for the persistence of second job holding using a dynamic panel model. Further, I identify significant gender differences in the decision to moonlight, where especially women in the lower part of the earnings distribution and women with few years of tenure are most likely to take up a second job.

JEL-Classification: J22; J28

Keywords: second job, marginal second job, multiple job holding

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1 Introduction

Second job holding, also referred to as moonlighting, is a notable labour market feature and is the topic of numerous studies documenting substantial numbers of the work force engaging in more than one job in most industrialized countries (recent studies include Auray *et al.*, 2021, and Choe *et al.*, 2017).

Standing out among other Western countries is Germany, where examining German data over the recent almost two decades suggests an unseen upward swing in second job holding, more than doubling in numbers and being the exception in comparison to other European countries (Klinger and Weber, 2020). This unique trend started after a change in the German legislation allowed for extensive dispensation of marginal employment, including marginal second jobs, from taxes and social security contributions starting in 2003. Figure 1 illustrates this strong increase and shows that in 2019 more than 2.5 million employees in Germany held at least one additional job, translating into about 9% of the employed with at least one job subject to social security. As noted by Klinger and Weber (2020) evidence for the German labour market is scarce and somewhat outdated (Heineck, 2009, and Schmidt and Voss, 2014)[1], regarding the increase of second job holding over the last 15 years.

Turning to the existing literature, in general the reasons for holding multiple jobs can be characterized by two main motives. The so-called hours constraint (or earnings constraint) motive applies to workers being unable to supply their desired number of hours in a first job, which leads them to taking up an additional job to optimize their individual labor supply (e.g. Shishko and Rostker, 1976; Conway and Kimmel, 1998). Early research found that specifically workers' earnings on the first job determined the propensity to moonlight and concluded that people foremost take up additional jobs to increase living standards and meet financial needs (e.g. Hamel, 1967; Guthrie, 1969), as for example labor market institutions constrained the hours in their primary occupation (Perlman, 1966). Furthermore, Boheim and Taylor (2004) showed that higher income

[1] The study by Heineck (2009) uses SOEP data up to the year 2005 and Schmidt and Voss (2014) use SOEP data up to 2011.

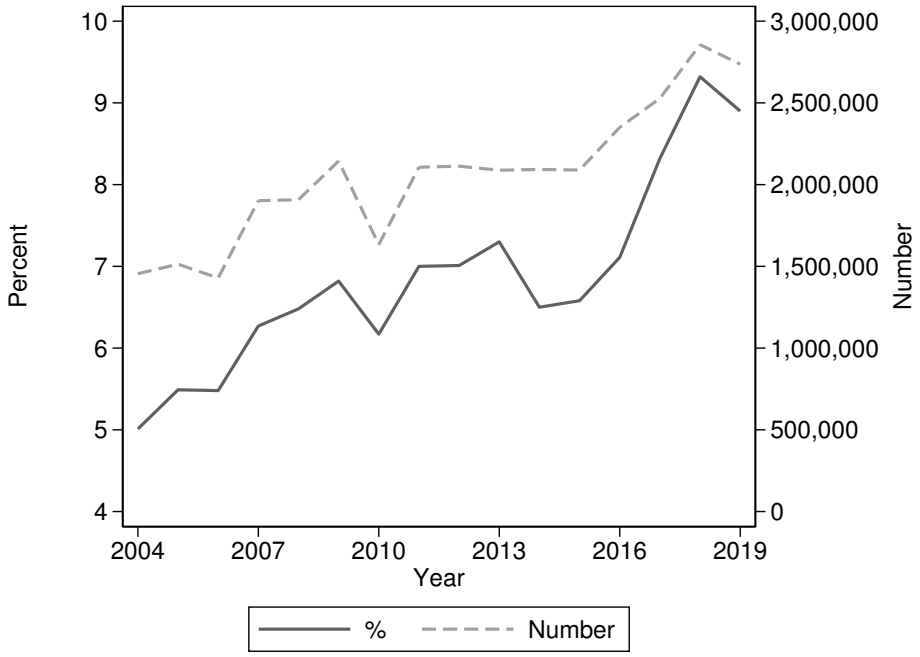

Figure 1: Share and number of employed having a second job (SOEP 2004-2019; weighted using sample weights)

levels in the first job decreased the propensity to take up a second job and also found that second jobs are not only temporary labor supply adjustments but rather persist over time.

Alternatively, the heterogeneous jobs (or portfolio) motive accounts for workers who do not face an hours constraint on their first job, but choose to work a second job for reasons beyond earnings. Workers may increase their utility from different aspects of the second job then just income alone, since there exist complementarities with the first job, e.g. the professor who also works as a consultant or a mother who holds two jobs to meet time-allocation needs (Heineck, 2009). Moreover workers may aim at diversifying their tasks to increase satisfaction by engaging in more pleasant or prestigious second jobs (Conway and Kimmel, 1998, and Renna, 2006) or invest in human capital (Averett, 2001). Empirical work supporting the portfolio motive includes Panos *et al.* (2014) showing that the acquired skills from the second job increase the probability of finding a new job or Pouliakas (2017) finding high-skilled moonlighters upgrading their skills. Auray *et al.* (2021) find that second job holding is rising with individuals' education and interpret their results as evidence for a comparative advantage of educated workers in second job

holding. Allen (1998) (for the US) and Boheim and Taylor (2004) (for the UK) obtain that constrained workers are actually less likely to hold an additional job than unconstrained workers, thus suggesting that heterogeneous job motives are more important than the hours constraint. Other studies exploring the determinants of multiple job holding include Kimmel and Conway (2001), Wu *et al.* (2009) and Dickey *et al.* (2011).

Investigating economic conditions and moonlighting, Amuedo-Dorantes and Kimmel (2009) find for the US that multiple job holding of men is largely acyclic, while female multiple job holding switched to being procyclical in the early 2000s. Similarly, Hirsch *et al.* (2017) document that multiple job holding is largely acyclic and negligible in mitigating earnings volatility over the business cycle. Moreover it is rather unresponsive to unemployment or employment growth changes within markets over time.

Against this backdrop, this paper contributes to the existing literature as follows. Firstly, using recent panel data for Germany I document developments in second job holding since the legislative change in 2003 with a focus on marginal second jobs and how these vary especially between men and women. Secondly, I show empirically that second job holding is a persistent feature of workers' biographies in Germany. Thirdly, I investigate the individual determinants of taking up a second job—either a marginal or non-marginal one—and whether there are marked differences among specific groups of workers.

The remainder of this paper is organised as follows. Section 2 describes my data and provides descriptive findings on the prevalence and extent of second job holding in Germany. Section 3 explains the econometric approach based on a dynamic multinomial logit random effects model. Section 4 presents and discusses my estimation results, and Section 5 concludes.

2 Data and descriptive findings

Within the German labour market there is the distinction into two different types of employment: regular jobs subject to income tax and social security contributions, and marginal jobs (called mini-jobs), which are exempt from income taxes and the employee

share of social security contributions (health, long-term care, unemployment, and pension) leading to 'gross is net' pay for those jobs. From 1999 to 2003 the social security exemption for marginal employment additional to the main job had been abolished and when holding a second job, these earnings were added to the main job earnings and were thus subject to income tax and social security contributions. The law governing marginal employment was changed with the Hartz II reforms, effective April 1, 2003, and introduced a marginal earnings threshold of 400 Euros and removed the limit of 15 hours per week for marginal employment and allowed workers in a regular main job to hold an additional marginal second job free of tax and social security contributions. As a result of legislative changes in the area of marginal employment, the monthly earnings limit for marginal employment was raised from 400 to 450 Euros as of January 1, 2013. At the same time, these mini-jobs became subject to compulsory insurance in the statutory pension insurance, but the option to be exempt was created. Thus, second job holding in Germany can be divided into holding a marginal (400/450 Euros per months up to 2013/from 2013 onwards) or non-marginal second job (exceeding 400/450 Euros per month). Therefore, I use the earnings information on second jobs in my data to define these second jobs according to these thresholds, meaning into marginal and non-marginal second jobs.

My data come from the German Socio-Economic Panel (SOEP henceforth) for the years 2003[2] to 2019 (Goebel *et al.*, 2018). This survey is nationally representative and provides detailed information on individuals and households on an annual basis. The same individuals are re-interviewed each year, and if they leave their original households to form new households all adult members of these new households are also interviewed. I include only employees that have a primary job, which is subject to social security contributions, meaning this income must exceed 400 (450) Euros per month for the years up to 2013 (after 2012). Furthermore the sample is restricted to workers aged 18 to 65 who are full- or part-time employed on the first job. I exclude self-employed[3], apprentices, interns, and partial retirees.

[2] I only include observations for the year 2003 with the interview time being later than April 1st, since from that time on the legislative change was in effect.

[3] I exclude self-employed in the main job as they have more flexibility of choosing their working hours and other aspects of their job.

Table 1: Variable means by second job status

	Main job only		Marginal 2nd		Non-marginal 2nd	
Main job characteristics	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
Main job monthly gross income in €	3,332.59	2,209.68	3,258.94	1,889.72	4,309.28	2,445.93
Decile of first job gross income (1/0):						
Up to 1st decile	0.025	0.166	0.030	0.251	0.023	0.169
1st to 2nd decile	0.044	0.152	0.043	0.175	0.040	0.119
2nd to 3rd decile	0.077	0.141	0.065	0.156	0.048	0.116
3rd to 4th decile	0.092	0.108	0.092	0.111	0.041	0.116
4th to 5th decile	0.109	0.099	0.115	0.085	0.069	0.083
5th to 6th decile	0.115	0.090	0.138	0.065	0.083	0.077
6th to 7th decile	0.125	0.084	0.128	0.062	0.118	0.075
7th to 8th decile	0.131	0.073	0.136	0.046	0.112	0.089
8th to 9th decile	0.141	0.056	0.138	0.034	0.165	0.092
Above 9th decile	0.141	0.031	0.117	0.015	0.301	0.064
Tenure (1/0)						
Less than 2 years	0.155	0.177	0.156	0.249	0.134	0.196
2-5 years	0.167	0.185	0.175	0.217	0.158	0.208
5-10 years	0.178	0.185	0.179	0.204	0.183	0.210
More than 10 years	0.500	0.453	0.489	0.330	0.525	0.387
Full-time (1/0)	0.950	0.527	0.891	0.385	0.842	0.413
Temporary contract (1/0)	0.193	0.201	0.185	0.200	0.205	0.233
Public service sector (1/0)	0.225	0.357	0.331	0.357	0.400	0.452
Worker characteristics						
Family status (1/0)						
Single and no children	0.184	0.188	0.198	0.226	0.134	0.188
Partner and no children	0.366	0.409	0.331	0.337	0.356	0.402
Partner and children	0.433	0.318	0.457	0.323	0.494	0.319
Single and children	0.017	0.085	0.014	0.114	0.016	0.091
Preferred working hours first job (1/0)						
More hours	0.261	0.257	0.323	0.396	0.361	0.347
Less hours	0.292	0.319	0.282	0.254	0.294	0.294
Same hours	0.447	0.424	0.395	0.350	0.345	0.358
Employment status partner (1/0)						
No working partner	0.517	0.526	0.511	0.608	0.526	0.604
Full time	0.194	0.446	0.175	0.368	0.147	0.376
Part time	0.239	0.020	0.232	0.017	0.282	0.016
Other	0.051	0.008	0.082	0.008	0.045	0.005
Age (1/0)						
18-25 years old	0.046	0.049	0.044	0.048	0.018	0.013
26-35 years old	0.187	0.178	0.200	0.180	0.119	0.155
36-45 years old	0.301	0.303	0.316	0.302	0.330	0.305
46-55 years old	0.308	0.324	0.316	0.354	0.334	0.377
Older than 55 years	0.157	0.146	0.125	0.116	0.199	0.150
Skill level (1/0)						
Low skill	0.074	0.072	0.074	0.073	0.029	0.038
Medium skill	0.660	0.649	0.628	0.682	0.480	0.457
High skill	0.266	0.279	0.298	0.245	0.490	0.505
Lives in East Germany (1/0)	0.216	0.247	0.136	0.154	0.142	0.197
Migration Background (1/0)						
No migration background	0.815	0.838	0.806	0.824	0.891	0.862
Direct migration background	0.139	0.117	0.146	0.130	0.076	0.091
Indirect migration background	0.046	0.045	0.048	0.046	0.033	0.047
Number of Individuals	13,984	13,809	1,535	1,916	595	367
Number of Observations	60,654	57,994	3,209	4,036	1,258	639

Notes: SOEP 2003-2019; unbalanced panel, unweighted.

Table 1 tabulates the variable means for the estimating sample by second job status. The final sample comprises 127,790 observations (49% Women). The SOEP data include information on workers' personal and job characteristics. Moreover, the SOEP includes information on the household and family context of interviewed persons allowing me to include this information in later investigations. Workers characteristics comprise, *inter alia*, their sex, age, information on educational attainment, family status, employment status of partner, migration background, and whether the person lives in East or West Germany. Characteristics of the main job include workers' earnings, job tenure, temporary (as opposed to permanent) contract, working hours, whether the job is in the public service sector, occupation, industry sector, and firm size. For my further analysis I will make use of monthly income deciles (derived from monthly earnings across all observations by year) to allow for non-monotone income effects in latter models, as well as for descriptive evidence for different income groups. For workers' preferences regarding working hours, I can generate an appropriate indicator. SOEP-interviewees are asked: 'If you could choose your own working hours, taking into account that your income would change according to the number of hours: How many hours would you want to work?'[4]. Comparing this number of desired working hours with actual hours worked, gives me an indicator for the working hours preference of a worker.[5]

As is visible from Table 1, there are substantial differences between men's and women's characteristics and their second job status. Firstly, there are marked differences in monthly gross income by job status and gender. Men's income in the main, respectively only job, is in all cases higher than their female counterpart's. Comparing the incomes of workers with regard to what type of second job they hold, it shows that workers with a marginal second job tend to have lower incomes in their first job than those having a non-marginal second job. Note further that female marginal second job holders are disproportionally found in the lower main job income deciles compared to the other two outcomes, with almost 60% being in the lowest four deciles. Among male non-marginal second job holders, top earners

[4] This question is asked directly after questions relating to the first (main) job.

[5] Information on desired working hours is not available for 2019. Therefore latter estimations include data from 2003 to 2018.

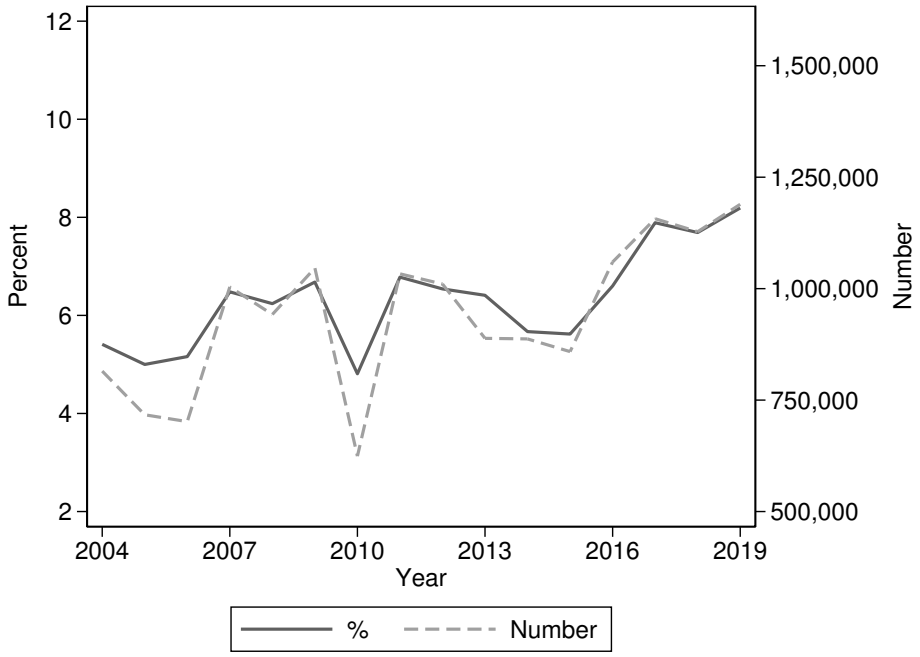

Figure 2: Male share and number of employed having a second job (SOEP 2004-2019; weighted using sample weights)

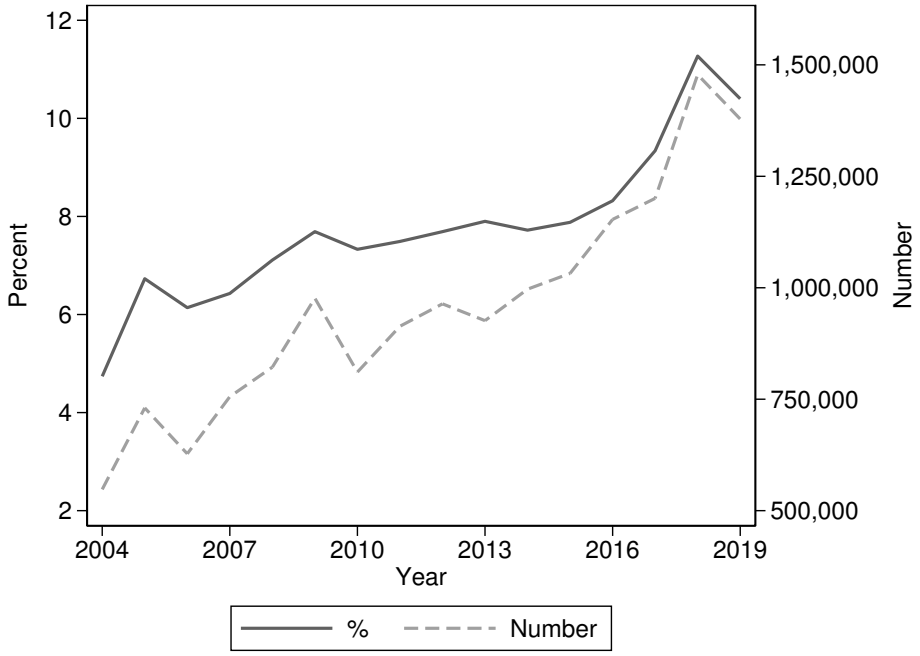

Figure 3: Female share and number of employed having a second job (SOEP 2004-2019; weighted using sample weights)

make up the largest group with almost 50% being in the top two deciles. Moreover, female as well as male moonlighters work less often full time than employees with only one job.

Turning to workers' personal characteristics, we see from Table 1 that the proportion of single mothers is higher for second job holders, whereas among male marginal second job holders the proportion of men with partner and children is highest. About one third of second job holders prefers more hours in their main job, which could be an indication of the hours constraint. The distribution of skill levels is quite similar for workers with only one job and marginal second job holders, whereas among non-marginal second job holders the share of low skilled is smallest. Apart from that, we can see that the share of second job holders is smaller in Eastern Germany.

In the following, using these data and the provided sample weights, I will descriptively investigate trends and heterogeneities in second job holding for Germany for the years 2004[6] to 2019 for various subgroups. Note that I will mainly focus on marginal second jobs in this descriptive analysis, since for those jobs legislative changes were introduced.

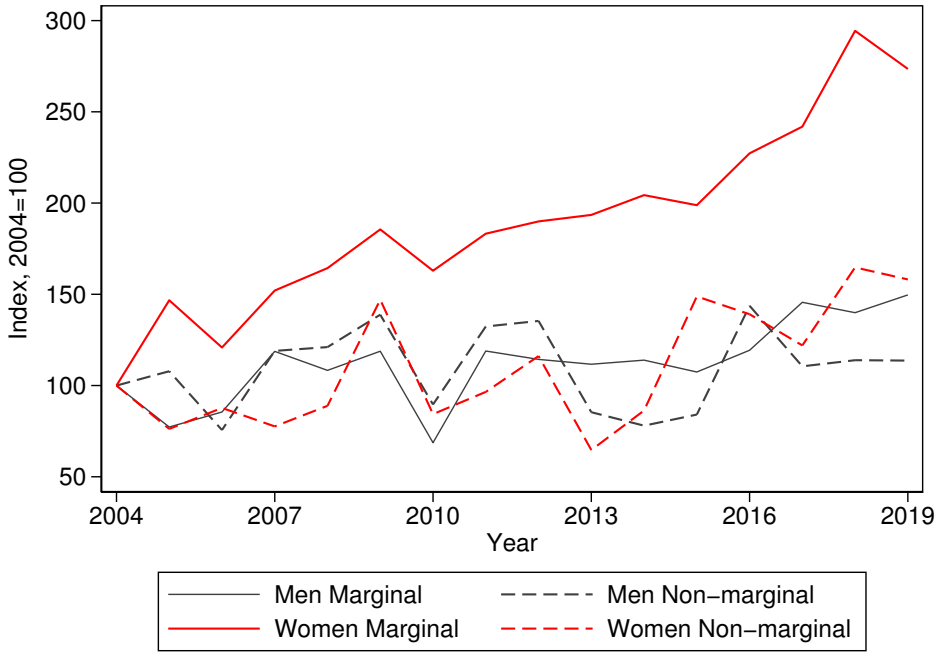

Figure 4: Development of second job types for men and women (SOEP 2004-2019; weighted using sample weights)

[6] I start with the year 2004 as I am comparing absolute yearly numbers and for the year 2003 that number would be very small, due to the legislative change in April 2003 and only a small number of SOEP interviews for the year 2003 after April of this year.

Having seen the strong overall increase in second jobs in Germany, Figures 2 and 3 show these developments separately for men and women. Men exhibited in 2004 initially a higher number of moonlighters than women in absolute and relative terms, but have been subsequently overtaken by women. From 2004 to 2019, the share of women holding more than one job rose from around 4 to more than 10 percent, whereby the absolute number almost tripled. The increase in the share of moonlighting men was moderate from about 6 to about 8 percent, since the legislation on mini-jobs changed. The number of men holding a second job increased during this period by about half a million. In addition to that, there is a visible dip in male second job holding for the year 2010, the time of the financial crisis and sharp drop of economic growth in Germany.

Table 2: Number of second job holders by second job type

	Men		**Women**	
Year	2004	2019	2004	2019
Marginal second job	635,000	950,000	445,000	1,215,000
Non-marginal second job	210,000	240,000	105,000	165,000

Notes: SOEP 2004-2019; weighted using sample weights.

However, as pointed out before, there are two different types of second jobs in Germany; marginal and non-marginal ones. Figure 4 illustrates the development of these different second job types by gender. It stands out, that in particular marginal second jobs of women have increased. This increase is almost threefold and by far the strongest one during the considered time period. Whereas women's non-marginal second job numbers have increased by about 50 percent, we can see that men's non-marginal second job holding remained about the same, with some ups and downs during these years. Table 2 gives an indication of the magnitude of moonlighting workers, and further shows that marginal second jobs substantially outnumber non-marginal ones. Taking into account the increased female participation rate and also the strong German economic performance for the second part of my observation period, these descriptive findings nevertheless appear very plausible in connecting these increases to the legislative changes. It also shows that non-marginal second employment is rather unaffected.

Next, I will take a closer look at those marginal second job holders and who they

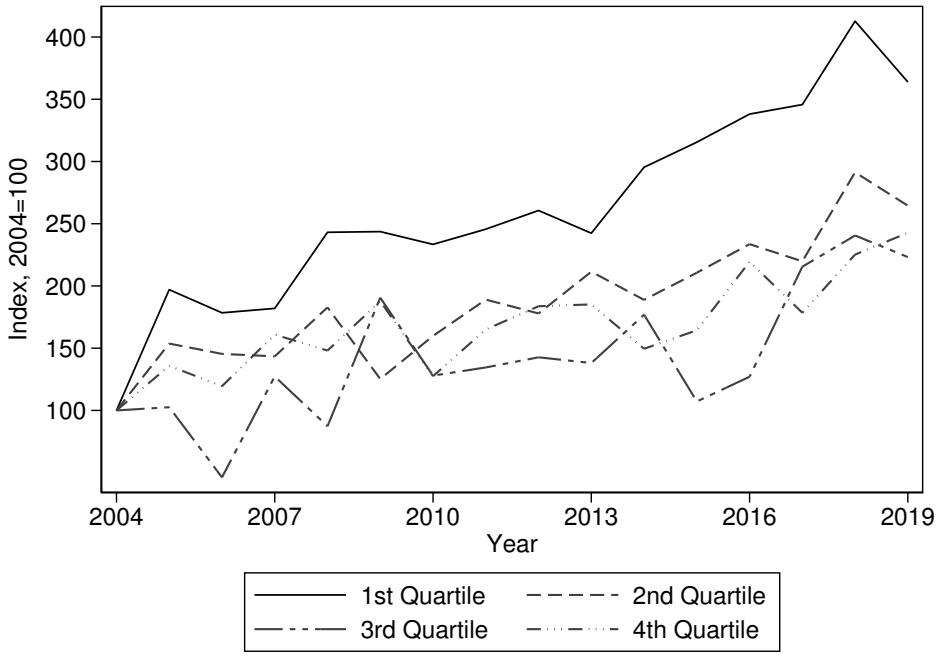

Figure 5: Development of marginal second job holding by monthly income quartiles for women (SOEP 2004-2019; weighted using sample weights)

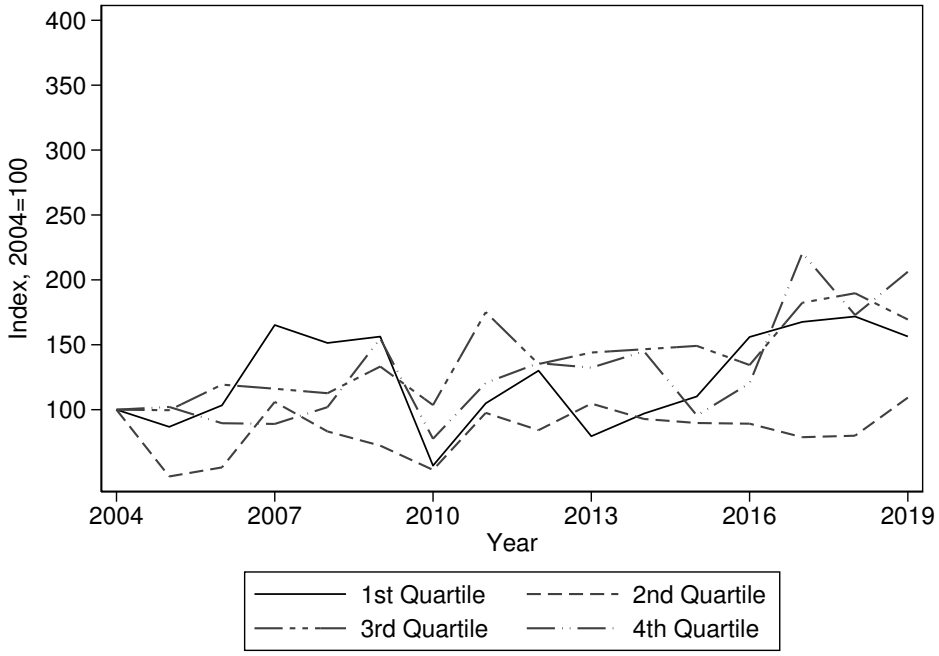

Figure 6: Development of marginal second job holding by monthly income quartiles for men (SOEP 2004-2019; weighted using sample weights)

are. Figure 5 shows the development of marginal second job holding of women divided into monthly first job income quartiles of the whole distribution (including both men and women). The number of marginal second jobs is trending upwards for all income quartiles, but is largest for the lowest income quartile by a large margin. In 2019 there are three and a half times as many female marginal second job holders in the lowest income quartile than were in 2004. For the second quartile the number increased by more than 150%, while it also doubled for female top earners. On the contrary, the numbers of male marginal second job holders (Figure 6) are quite similar for all income quartiles but the second quartile, where second job holding even seems to decline over the years.

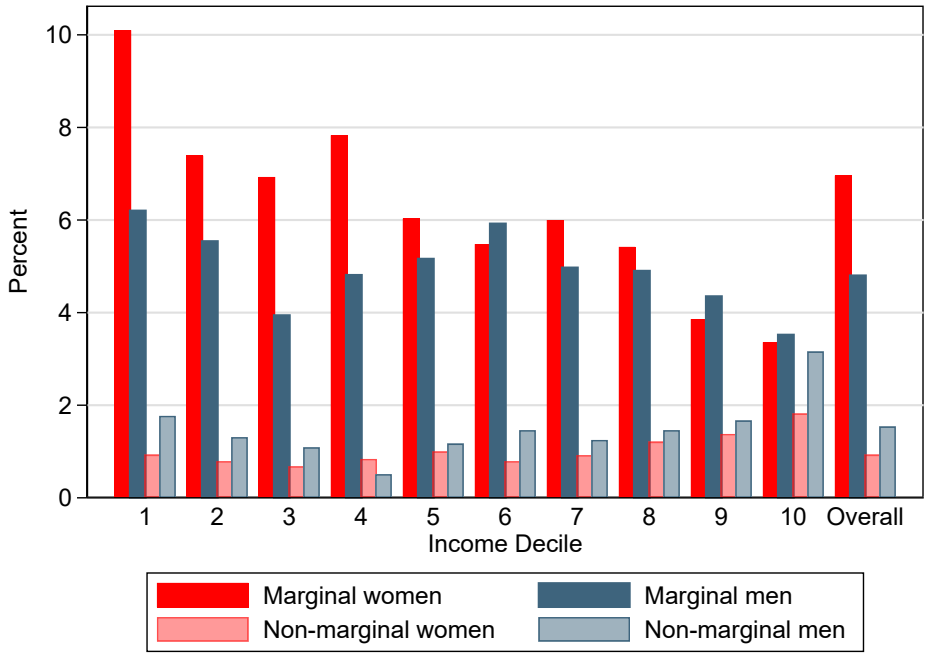

Figure 7: Share of second job holders by type and income decile (SOEP 2003-2019; weighted using sample weights)

This impression is also borne out in Figure 7 that shows the shares of marginal and non-marginal second holders for income deciles by gender. The lower income deciles of women have the highest share of marginal second job holders with every tenth women in this group moonlighting, while this share is decreasing when moving up the income distribution. Within the lower half of the income distribution, the share of women in marginal second jobs is always higher than for men. About 6% of male workers in the first income decile also engage in a marginal second job, with another peak for the sixth decile.

Overall, I can see that the incidence to hold a marginal second job (mostly) decreases along the income distribution no matter the gender of the worker. As seen before, non-marginal second job holding plays a minor role with shares between 1 or 2 percent, with the exception being the top decile for men, where it is almost on par with marginal second job holding.

In addition to differences in second job holding for specific income groups, I look at the development of marginal second jobs for specific skill levels of workers. I distinguish high-skilled workers with an academic education, medium-skilled workers with a vocational training, and low-skilled workers with neither. Figure 8 displays that marginal second jobs of women of all skill levels more than doubled over the considered time span; showing a very similar upward trend. By contrast, we can see in Figure 9 that especially low skilled men increased their engagement in marginal second jobs. For the medium skilled (the largest skill group) there is almost no change noticeable across the years, while for the high skilled it rose by about 50 percent.

Table 3: Share of marginal second job holders by family status for women and men

	Income decile										
Family status of women	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Overall**
Single	10.32	9.43	8.7	9.91	7.31	6.36	8.16	4.29	4.33	7.55	7.89
Partner	9.96	6.47	5.6	7.04	5.04	4.68	4.35	6.49	3.78	1.21	6.13
Partner and children	10.02	6.79	6.05	5.29	5.97	5.8	5.24	4.33	3.54	3.3	6.85
Single with children	10.77	8.97	10.52	11.69	6.5	5.74	6.23	7.16	1.9	2.7	8.93
Family status of men											
Single	7.01	6.15	4.69	5.25	5.61	7.45	4.91	4.14	4.6	2.53	5.24
Partner	6.97	4.74	3.06	3.8	4.17	5.49	4.85	4.1	4.02	3.31	4.26
Partner and children	4.61	6.08	4.12	5.68	5.85	5.11	5.26	6.52	4.65	4.11	5.18
Single with children	0.88	1.94	2.96	2.23	6.23	7.62	2.09	0.24	3.49	7.99	3.12

Notes: SOEP 2003-2019; weighted using sample weights.

In order to take further advantage of the strength of the SOEP data, I will look at the composition of marginal second job holders with regard to their family status (Table 3). As already seen, the share of women with a marginal second job is higher than those of men no matter the family status. Single mothers and single women show the highest shares of marginal second job holders with 9 respectively 8% among them. This fact is

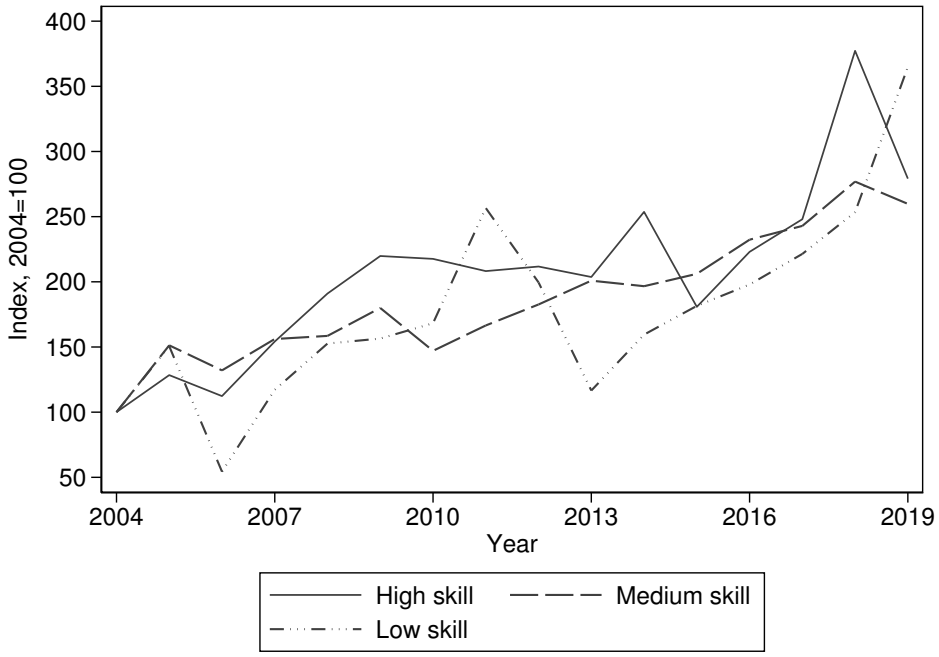

Figure 8: Development of marginal second job holding by skill level for women (SOEP 2004-2019; weighted using sample weights)

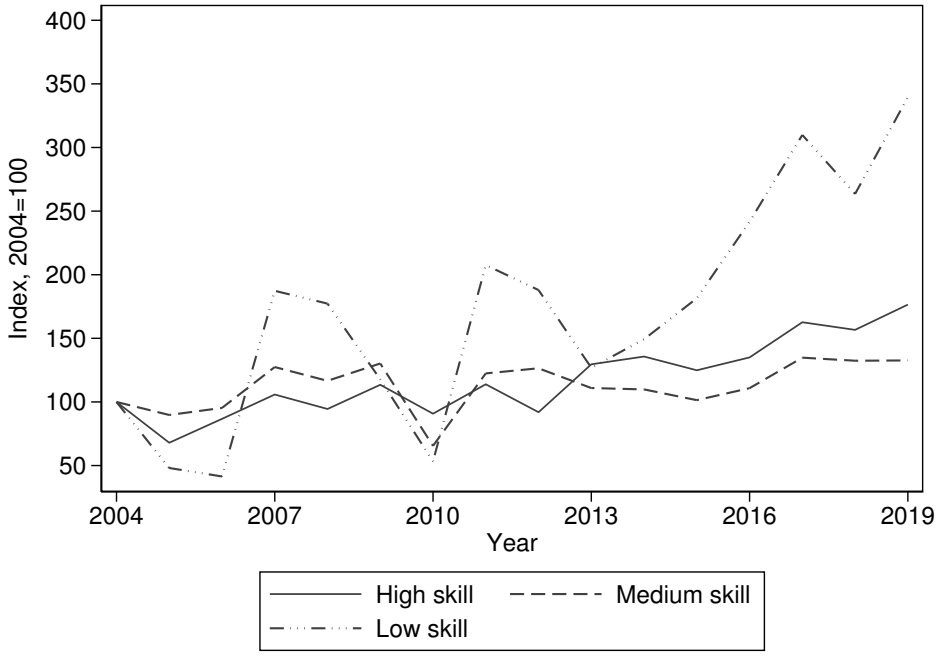

Figure 9: Development of marginal second job holding by skill level for men (SOEP 2004-2019; weighted using sample weights)

even exacerbated when considering the lower income deciles. Further, we see that workers having children with a partner present a higher share of marginal second job holders than those without children. Taking a closer look at the different income deciles shows that the share of marginal moonlighters follows a downward trend while income rises across all groups.[7] All of these findings let me conclude so far, that when workers' conditions are below average or less than ideal, regarding e.g. income or household composition, marginal second jobs are particularly prevalent.

Table 4: Hours worked per week by job combination

	Only main job	**Marginal second job**	**Non-marginal second job**	**Overall**
Men				
Hours main job	42.9	41.8	43.2	42.9
Hours in second job	—	5.4	8	6.1
Women				
Hours main job	35	32	33	35
Hours in second job	—	5.5	8.5	5.9

Notes: SOEP 2003-2019; unweighted.

In addition, I want to make use of the data to show the allocation of working hours between the main and the second job. Firstly, Table 4 tabulates the mean hours worked per week and job combination. Those who have a marginal second job work on average fewer hours in their main job than those without a second mini-job, which provides some suggestive evidence for the hours constraint motive of moonlighting for this group. Here, women with a marginal second job work 3 hours less on average in their first job than women with only one job. Regardless of gender, workers with a marginal second job allocate on average 5.5 working hours per week to this second job. Men work more hours in their main jobs than women and seem to reduce these hours by not as much as women when holding an additional mini-job. Non-marginal second job holders work on average more hours in the main job than those with a marginal second job, whereas male non-marginal second job holders seem to be workers with higher working hours across the

[7] Single fathers are the exception, but are only very few in numbers in the data

board compared to the other types. This lends some evidence to the fact that particularly men with higher paying (more hours intensive) main jobs hold additional jobs with higher additional earnings opportunities.

As one of the main questions of this paper is the persistence of second job holding, I look at the transition matrix for second job holding. Looking at Table 5 the data seem to confirm this persistence. About 60% of workers that had a marginal second job in one year also had one in the next year. Also, about 54% of non-marginal second jobbers also had one in the next year. Apart from that, very few workers (about 3%) start any type of second job from year to year. Furthermore, it rarely occurs that workers switch from a marginal to a non-marginal second job in the next year. On the other hand, the opposite holds true for about 20% of non-marginal second jobbers. If we were to look at gender differences, all these numbers are somewhat larger for women than men.

Table 5: Transitions between main job and second job combination types

	Period t		
	Only main job	Marginal second job	Non-marginal second job
Period t-1			
Only main job	97.25	2.27	0.48
Marginal second job	35.85	59.01	5.14
Non-marginal second job	27.22	19.06	53.72
Total	92.51	5.91	1.57

Notes: SOEP 2003-2019; unweighted data; 162,577 observations from 33,747 individuals; figures indicate row percentages.

In summary so far, my descriptive findings show a strong increase in marginal second jobs in Germany. They further document significant differences in marginal second job holding across different socio-economic worker groups, where especially low income and low skill workers hold a marginal second job. What is more, there is descriptive evidence for a considerable persistence of second job holding. In a next step, I will run regressions to quantify the contribution of specific characteristics to the persistence and take-up of a second job.

3 Econometric Approach

In a first step, I investigate in a binary response model I investigate which characteristics are correlated with starting a marginal second job. I focus on marginal second jobs only, because no meaningful regression analysis is feasible for non-marginal second jobs due to the very low number of people starting a non-marginal second job in my sample. Moreover, the legislative change only affected marginal second jobs. Since taking up such a marginal second job is rare, I choose a complementary log-log model, which is asymmetrical and thus suitable for modelling such rare events.

In a next step, my econometric approach to study persistence rests on a dynamic random-effects logit model. I translate the decision to hold a second job into a multinomial logit setting to distinguish between types of second jobs and explore the factors driving a worker's decision to have either a main job, the main and a marginal second job, or a main and a non-marginal second job. Using a dynamic specification accounts for the state dependence of workers, modeled as a $t-1$ lag in my outcome variable.

In such a model, identifying true state dependence rests on the assumption of no correlation between unobserved heterogeneity and the outcome variable. Another issue is the initial condition problem stemming from the correlation between the relevant unobserved factors and the initial observation y_{i0}. The initial period y_{i0} in my data regarding second jobs might not (and likely does not) correspond to the beginning of the stochastic process leading to the second job engagement. Therefore, the approach of the model I am using is based on the simple solution to the initial condition problem by Wooldridge (2005) and the extension by Rabe-Hesketh and Skrondal (2013) and means that I include the initial value of the response variable and of other time-varying explanatory variables, as well as within-unit averages of the time-varying explanatory variables.

Following this, my model has the following specification:

$$y_{it} = \gamma \mathbf{Z}_{it} + \rho y_{it-1} + c_i + u_{it} \tag{1}$$

The outcome variable y_{it} expresses the chances of holding a particular job type combination for worker i at time t.[8] $\mathbf{Z}_{it}$ is a set of time-varying explanatory variables considered strictly exogenous, conditional on the unit-specific unobserved effect c_i. ρ captures the coefficient for the y_{it-1} and thus true state dependence, while u_{it} is an error term.

As Rabe-Hesketh and Skrondal (2013) note, the unit-specific unobserved effect c_i can be written as:

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \overline{\mathbf{Z}}_i \alpha_2 + \mathbf{Z}_{i0} \alpha_3 + a_i \tag{2}$$

where $\mathbf{Z}_{i0}$ and y_{i0} represent the initial values of the time-varying explanatory variables and of the response variable, respectively.[9] $\overline{\mathbf{Z}}_i$ comprises the within-unit averages of the explanatory variables where the averages are based on all periods. Lastly, a_i is a unit-specific time-constant error term, normally distributed with mean 0 and variance σ_a^2. If the assumption holds, that unobserved heterogeneity is captured by c_i, then the lagged value of the response variable can be interpreted as true state dependence, meaning as the effect of holding a second job in one period on the second job status in a subsequent time period.

As covariates I add the following groups of variables: (i) main job characteristics including groups of dummies for income deciles, tenure, full-time hours, a temporary contract, public-service sector, as well as dummies for occupation, sector, and firm size; (ii) worker characteristics capturing family status, hours preferences, educational attainment (distinguishing high-skilled workers with an academic education, medium-skilled workers with a vocational training, and low-skilled workers with neither), employment status of the partner, age, migration background, and residence in East Germany. I employ dummies for the wage deciles as an explanatory variable to allow for non-monotone income effects suggested by the descriptive analysis in Section 2. I further control for working time arrangements (full- vs part-time) to disentangle both effects.

[8] Note that $t = 0$ indicates the initial period.

[9] They also show that this can be safely implemented in case of an unbalanced panel.

4 Estimation Results

First, I show the results for characteristics which correlate with workers to take up a marginal second job (Table 6).[10] Therefore I use a complementary log-log model to investigate the workers that take up a marginal second job in period t after working only their main job in $t-1$ and note in passing that my findings remain robust when using a standard logit model.

At first, I discuss female workers. Having controlled for other influences like family status or working full-time, the probability of starting a marginal second job is by far the highest in the lowest income and lowest tenure group. Compared to the top 10% of high-earners, the lowest income decile workers are 2 percentage points more likely to hold a marginal second job. This translates into an about one third increase in the average probability to have a marginal second job and thus by no means a small effect as the overall average marginal second job rate form women is around 6% in the sample. The same effect size can be seen for women with less than 2 years of tenure compared to women with tenure of 10 years and more. Furthermore income growth has an impact, since moving up in the income distribution shrinks the probability of a marginal second job slowly but steadily, as staying longer with an employer does as well. This is consistent with the results of Klinger and Weber (2020) that document a similar pattern and conclude no evidence for the heterogeneous/ portfolio motive of moonlighting, since financial needs seem to dominate.

Other things being equal, full-timers and women with a partner are less likely to take up a marginal second job. The fact, that a woman wants to work more hours instead of the same number of hours in the main job increases the probability to take up a marginal second job by 1.4 percentage points, and further points at a possible hours, respectively earnings, constraint motive for the second job. Age plays a minor role for women to look for a marginal second job, as I can only see that women over the age of 55 are marginally less likely to do so. Living in East Germany reduces the average probability to engage in a marginal second job by 25% or 1.3 percentage points, which is highly likely due to a

[10] See Appendix A.1 showing coefficients and standard errors.

Table 6: Complementary log-log model for holding a marginal second job after only main job in period t-1; marginal effects

	Women	**Men**
Main job characteristics		
Main job monthly gross income		
up to 1st decile	0.019***	0.008
1st to 2nd decile	0.014***	0.013**
2nd to 3rd decile	0.014***	0.008**
3rd to 4th decile	0.012**	0.009**
4th to 5th decile	0.011**	0.012***
5th to 6th decile	0.009*	0.009***
6th to 7th decile	0.004	0.006**
7th to 8th decile	0.006	0.007***
8th to 9th decile	0.004	0.002
above 9th decile (reference)	—	—
Tenure		
less than 2 years	0.022***	-0.001
2-5 years	0.011***	-0.001
5-10 years	0.008***	-0.003
more than 10 years (reference)	—	—
Full-time (1/0)	-0.006***	-0.007**
Fixed-term contract (1/0)	0.003	0.002
Public service sector (1/0)	0.002	0.006**
Personal characteristics		
Family status		
Single and no children (reference)	—	—
Partner and no children	-0.007***	0.001
Partner and children	-0.004	0.002
Single and children	0.001	0.002
Preferred working hours first job		
More hours	0.014***	0.006***
Same hours (reference)	—	—
Less hours	0.002	0.001
Employment status partner		
Full time (reference)	—	—
Not working	0.008***	0.001
Part time	0.01	0.002
Other	0.022**	0.011***
Age		
18-25 years old	0.004	0.014**
26-35 years old	0.009***	0.013***
36-45 years old	0.007*	0.008***
46-55 years old	0.009***	0.005***
older than 55 years (reference)	—	—
Skill level		
Low skill	-0.006*	-0.006**
Medium skill (reference)	—	—
High skill	-0.007***	-0.002
Lives in East Germany (1/0)	-0.013***	-0.010***
Migration Background		
No migration background (reference)	—	—
Direct migration background	0.004	-0.001
Indirect migration background	-0.005	-0.004
	44,476 obs./ 10,679 persons	48,086 obs./ 11,045 persons

Notes: SOEP 2003-2018. Standard errors clustered at the person level (* p<0.05, ** p<0.01, *** p<0.001). Controls included for industry sectors, occupation, firm size and years.

higher share of full-time working women than in Western Germany.

Table 6 shows that men in the middle of the income distribution are most likely to start a second job, e.g. men in the fifth income decile have a 1.2 percentage points or 35% higher probability to have a marginal second job than top male earners. Moreover, men working in the public service sector have a 15% higher average probability to engage in a marginal second job compared to those in the private sector. This might be explained by hours and job security in the public sector job. I also find that the desire to work more hours, as well as being in prime working age, increases the chances to engage in an additional mini-job. As was the case for women, living in East Germany reduces the probability to moonlight.

In summary, I conclude that in particular a less than ideal first main job environment (income, tenure, part-time) of women appears to be a good indicator of taking up an additional mini-job.[11] For men the same can be said for average income levels and working in the public-service sector. On the one hand, the hours constraint motive or probably better earnings constraint motive gets support by the fact that workers with a preference to work more hours show a higher probability to look for an additional marginal job, where gross pay is net pay. On the other hand, the portfolio motive is hardly confirmed, as the probability to hold a second job does not rise significantly towards the top of the wage distribution.

Next, in Table 7 I present the marginal effects of the dynamic multinomial logit model with random effects for different second job status types of German workers.[12] The main variables of interest are the lagged second job states. Once controlled for the initial condition and net of the role of unobserved heterogeneity, these coefficients indicate the presence of significant genuine state dependence.[13]

Holding only the main job in $t-1$ serves as the reference category, such that the

[11] This is in line with the findings of Schmidt and Voss (2014) for the period up to 2010.

[12] The sum of the marginal effects for the alternatives: marginal second job and non-marginal second job, yield the respective marginal effect of the alternative: only the main job.

[13] See Appendix A.2 showing coefficients and standard errors.

reported marginal effects must be interpreted relative to this group. I observe a genuine state dependence for second job holders, where the state dependence is even more pronounced for women: having a marginal second job in year $t-1$ increases the probability of holding a marginal second job in year t by about 17 percentage points or 200% for women and 11 percentage points for men (keeping in mind that the average probability of holding a marginal second job is about 6% for women and 4.4% for men across my sample). The effect of having a non-marginal second job in $t-1$ on having a marginal one the year after is almost equal in size and also highly significant. Having a marginal second job or, respectively, a non-marginal second job in $t-1$ also increases the probability to hold a non-marginal second job in t by 3, or 5 percentage points respectively. The same pattern can be found for men, but the effect of state dependence regarding marginal second jobs is only about two thirds of the effect size of women. These findings strongly support the argument that second job holding is no temporary but a persistent feature, in particular for German female workers with marginal second jobs.

Note that in this dynamic setting, genuine state dependence becomes the single largest (and most significant) contributor to the probability for holding some type of second job. Nevertheless, I want to comment on the impact of other variables as well, which are unfortunately not estimated very precisely due to the small number of observations for this outcome. Firstly regarding marginal second jobs, the probability to have a marginal second job is highest for the lower income deciles for women as well as men. For women, tenure of less than 2 years increases the probability of a marginal second job compared to longer tenured workers, while the desire for more working hours in the first job is associated with a higher probability to have a marginal second job, as expected. Moreover low skilled women show an 11 percentage points higher probability to hold a marginal second job than medium skilled women, while high skilled females are also more prone to hold a marginal second jobs than medium skilled ones. Meanwhile low skilled men are less likely to hold a second job than men with vocational training. Apart from that, living in East Germany reduces the probability for men to hold a marginal second job by almost 5 percentage points. Therefore, I can conclude that for my sample of German workers

Table 7: Dynamic Multinomial logit model with random effects for second job states; marginal effects

	Women		**Men**	
	Marginal	***Non-marginal***	***Marginal***	***Non-marginal***
State dependence t-1				
Only main job (reference)	—	—	—	—
Marginal second job	0.172***	0.032***	0.112***	0.030***
Non-marginal second job	0.165***	0.047**	0.108***	0.041***
Main job characteristics				
Main job monthly gross income				
Up to 1st decile	0.016	0.004	0.028*	0.013
1st to 2nd decile	0.010	0.002	0.014	0.015*
2nd to 3rd decile	0.007	0.001	0.009	0.010
3rd to 4th decile	0.007	0.002	0.011	-0.001
4th to 5th decile	0.004	0.000	0.016**	0.006
5th to 6th decile	-0.001	-0.001	0.009	0.001
6th to 7th decile	-0.006	-0.001	0.004	0.002
7th to 8th decile	0.001	-0.001	0.005	0.003
8th to 9th decile	-0.005	0.003	0.006	0.000
Above 9th decile (reference)	—	—	—	—
Tenure				
Less than 2 years	0.014**	0.001	-0.005	-0.001
2-5 years	0.004	-0.001	-0.002	-0.002
5-10 years	0.001	0.001	-0.005	0.002
More than 10 years (reference)	—	—	—	—
Full-time (1/0)	-0.010**	-0.005**	-0.008	0.000
Temporary contract (1/0)	0.002	-0.001	-0.002	0.003
Public service sector (1/0)	0.001	0.001	0.007	0.004
Worker characteristics				
Family status				
Single and no children (reference)	—	—	—	—
Partner and no children	-0.010	-0.001	-0.002	0.000
Partner and children	-0.007	-0.003	0.000	-0.004
Single and children	-0.003	-0.001	-0.007	0.010***
Preferred working hours first job				
More hours	0.008**	-0.001	0.002	0.002
Same hours (reference)	—	—	—	—
Less hours	0.001	0.002	-0.001	0.000
Employment status partner				
No working partner (reference)	—	—	—	—
Full time	-0.008*	-0.001	-0.006	0.000
Part time	-0.006	0.000	0.001	-0.001
Other	0.003	0.006	0.007	-0.003
Age				
18-25 years old	0.014	-0.006	0.013	0.007
26-35 years old	0.008	-0.004	0.005	-0.003
36-45 years old	0.000	-0.001	0.000	0.005
46-55 years old	0.003	0.000	0.003	0.002
Older than 55 years (reference)	—	—	—	—
Skill level				
Low skill	0.112	-0.005	-0.023	-0.012***
Medium skill (reference)	—	—	—	—
High skill	0.033	0.015	-0.007	0.016
Lives in East Germany (1/0)	0.003	-0.020**	-0.046***	-0.005
Migration Background				
No migration background (reference)	—	—	—	—
Direct migration background	0.004	0.000	0.006	-0.004*
Indirect migration background	0.001	-0.001	0.000	-0.007**
	41,103 observation/8,974 persons		43,329 observation/8,965 persons	

Notes: SOEP 2003-2018. Standard errors clustered at the person level (* p<0.05, ** p<0.01, *** p<0.001). Controls included for industry sectors, occupation, firm size and years. Coefficients for the initial condition, and the initial value and the within-unit averages of time-varying explanatory variables are not shown in the table.

second job holding is persistent and even more so marginal second job holding and that especially for women in lower income groups, with low skills, and less job security (low tenure) the odds to have a marginal second job are highest. Descriptively, we had already seen that these groups showed the strongest increase in numbers across my sample period.

Overall, these estimations let me conclude that the probability of taking up a marginal second job depends a lot on individual and job characteristics — but once a worker is in, she is in, meaning that state dependence is very large for second job holders in Germany.

5 Conclusions

This study analyzes true state dependence in second job holding of German workers as well as the development of second job holding in Germany using panel data from the SOEP after the legislative change in 2003. This change allowed extensive dispensation of marginal second jobs from taxes and social security contributions. To that end, I analyzed the trends in second job holding overall and divided into the different types of second jobs.

Descriptively, I saw that women are more prone to hold second jobs and that the strong increase in numbers was mainly driven by marginal second jobs also known as mini-jobs. I further observed that the pronounced increase in marginal second jobs was largest in relative terms for low income women. Also, the data showed that non-marginal second job holders are a minority and seem to be unaffected by the legislative change as expected.

Using this panel data and taking into account the initial conditions problem, I estimate a dynamic multinomial logit model with random effects. I find that there is true state dependence in second job holding, especially for marginal second employment. This state dependence is even more pronounced for women than for men. Moreover, I find in panel estimations that low income, low tenure, part-time, and hours constrained women have a higher probability to take up a marginal second job. In short, my results show that gender differences in second job holding exist and that women in particular responded to the legislative change, which allowed for tax and social security contribution exempt second jobs.

Klinger and Weber (2020) argue that individual factors explain the increase over time

only to a very small extent and the tax exemption of marginal second jobs sets wrong incentives. I tend to follow their interpretation regarding wrong incentives of marginal second jobs and would see some further disadvantages. First, mini-jobbers themselves are losing out on certain social security benefits for their work in marginal second jobs, e.g. unemployment insurance or pension. This can be critical, as we have seen that especially low income groups tend to take up these jobs. Moreover, marginal second jobs set the incentive to stay below a certain threshold in earnings, although the individual might be able to work more. Secondly, it is unclear whether the tax exemption is desirable from a social point of view since the state forgoes tax revenue, as well as social insurance contributions. Even if the benefit of additional earnings capacities for low income workers is desired, the question remains, why there is the necessity for tax free second employment of well to do earners.

I expect the upward trend in marginal second jobs to go on, since the earnings limit for marginal employment has been recently increased from 450 to 520 euros per month. This could be used in future research to test how workers react in allocating their hours and how this continues to shape second job holding in Germany.

A Appendix

Table A.1: Complementary log-log model for holding a marginal second job after only main job in period t-1

	Women	**Men**
Main job characteristics		
Main job monthly gross income		
up to 1st decile	0.82***	0.50
	(0.31)	(0.31)
1st to 2nd decile	0.67**	0.70***
	(0.30)	(0.25)
2nd to 3rd decile	0.68**	0.48**
	(0.30)	(0.22)
3rd to 4th decile	0.58*	0.53***
	(0.30)	(0.20)
4th to 5th decile	0.56*	0.69***
	(0.30)	(0.19)
5th to 6th decile	0.45	0.56***
	(0.30)	(0.18)
6th to 7th decile	0.21	0.38**
	(0.30)	(0.18)
7th to 8th decile	0.32	0.42***
	(0.31)	(0.16)
8th to 9th decile	0.25	0.16
	(0.31)	(0.15)
above 9th decile (reference)	—	—
Tenure		
less than 2 years	0.78***	-0.064
	(0.10)	(0.13)
2-5 years	0.46***	-0.041
	(0.093)	(0.11)
5-10 years	0.35***	-0.14
	(0.092)	(0.10)
more than 10 years (reference)	—	—
Full-time (1/0)	-0.25***	-0.34**
	(0.095)	(0.15)
Fixed-term contract (1/0)	0.11	0.083
	(0.10)	(0.15)
Public service sector (1/0)	0.079	0.29**
	(0.084)	(0.11)
Industry		
Agriculture (reference)	—	—
Energy	-0.63	-0.098
	(0.57)	(0.55)
Minig	0	-0.68
	(.)	(1.05)
Manufacturing	-0.52	0.27
	(0.36)	(0.38)
Construction	-0.24	-0.032
	(0.41)	(0.40)
Trade	-0.55	0.30
	(0.35)	(0.39)
Transport	-0.47	0.27
	(0.39)	(0.40)
Bank, Insurance	-0.39	0.53
	(0.39)	(0.43)
Services	-0.34	0.57
	(0.35)	(0.38)
Other	-0.10	0.20
	(0.40)	(0.53)

Table A.1 continued: Complementary log-log model for holding a marginal second job after only main job in period t-1

	Women	Men
Occupation		
Untrained worker (reference)	—	—
Semi-Trained worker	-0.43**	0.11
	(0.18)	(0.28)
Trained worker	-0.49**	-0.0077
	(0.24)	(0.28)
Foreman, group leader	-0.53	0.28
	(0.59)	(0.33)
Foreman	-0.16	-0.31
	(0.77)	(0.45)
Industry or factory foreman	-0.49	-0.21
	(1.03)	(0.46)
Salaried employee, unskilled without training	-0.20	0.34
	(0.17)	(0.32)
Salaried employee, unskilled with training	-0.46***	0.11
	(0.17)	(0.30)
Salaried employee, skilled	-0.49***	0.058
	(0.17)	(0.28)
Salaried employee, highly skilled or managerial duties	-0.15	0.12
	(0.20)	(0.30)
Salaried employee with extensive managerial duties	-0.25	0.70**
	(0.41)	(0.34)
Civil servant, lower level	0	0.011
	(.)	(0.61)
Civil servant, middle level	-0.49	-0.35
	(0.33)	(0.37)
Civil servant, upper level	-0.81***	0.089
	(0.28)	(0.34)
Civil servant, executive level	-0.72**	0.72**
	(0.37)	(0.36)
Firmsize		
less than 20 employees (reference)	—	—
20 to 199 employees	-0.29***	-0.15
	(0.084)	(0.12)
200 and more employees	-0.27***	-0.24**
	(0.082)	(0.12)
Worker characteristics		
Family status		
Single and no children (reference)	—	—
Partner and no children	-0.28***	0.043
	(0.10)	(0.13)
Partner and children	-0.13	0.11
	(0.11)	(0.12)
Single and children	0.033	0.082
	(0.11)	(0.30)
Preferred working hours first job		
More hours	0.51***	0.31***
	(0.073)	(0.088)
Same hours (reference)	—	—
Less hours	0.087	0.049
	(0.082)	(0.088)
Employment status partner		
Full time (reference)	—	—
Not working	0.32***	0.033
	(0.084)	(0.12)
Part time	0.37*	0.13
	(0.21)	(0.12)
Other	0.70***	0.51***
	(0.26)	(0.16)

Table A.1 continued: Complementary log-log model for holding a marginal second job after only main job in period t-1

	Women	**Men**
Age		
18-25 years old	0.20	0.78***
	(0.19)	(0.25)
26-35 years old	0.37***	0.73***
	(0.14)	(0.15)
36-45 years old	0.28**	0.50***
	(0.13)	(0.15)
46-55 years old	0.36***	0.32**
	(0.12)	(0.13)
older than 55 years (reference)	—	—
Skill level		
Low skill	-0.23*	-0.36**
	(0.13)	(0.17)
Medium skill (reference)	—	—
High skill	-0.27***	-0.089
	(0.10)	(0.12)
Lives in East Germany (1/0)	-0.59***	-0.70***
	(0.094)	(0.12)
Migration Background		
No migration background (reference)	—	—
Direct migration background	0.15	-0.062
	(0.097)	(0.13)
Indirect migration background	-0.20	-0.26
	(0.17)	(0.18)
Year		
2004 (reference)	—	—
2005	0.37	0.81**
	(0.32)	(0.38)
2006	0.31	0.63
	(0.32)	(0.40)
2007	0.45	1.09***
	(0.32)	(0.39)
2008	0.54*	0.83**
	(0.32)	(0.39)
2009	0.72**	0.82**
	(0.32)	(0.39)
2010	0.30	0.54
	(0.33)	(0.41)
2011	0.71**	1.15***
	(0.33)	(0.39)
2012	0.69**	0.85**
	(0.32)	(0.39)
2013	0.81***	0.81**
	(0.31)	(0.39)
2014	0.83***	0.88**
	(0.31)	(0.39)
2015	0.59*	0.92**
	(0.31)	(0.39)
2016	0.54*	1.06***
	(0.31)	(0.39)
2017	1.05***	1.62***
	(0.31)	(0.38)
2018	0.88***	1.19***
	(0.32)	(0.39)

Notes: SOEP 2003-2018. Standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001).

Table A.2: Dynamic Multinomial logit model with random effects for second job states

	Women		**Men**	
	Marginal	***Non-marginal***	***Marginal***	***Non-marginal***
State dependence t-1				
Only main job (reference)	—	—	—	—
Marginal second job	2.706***	3.017***	2.506***	2.258***
	(0.123)	(0.235)	(0.135)	(0.238)
Non-marginal second job	2.672***	3.496***	2.477***	2.640***
	(0.251)	(0.445)	(0.209)	(0.299)
Main job characteristics				
Main job monthly gross income				
up to 1st decile	0.495	0.774	1.114**	1.326*
	(0.427)	(0.933)	(0.483)	(0.709)
1st to 2nd decile	0.317	0.425	0.693*	1.348**
	(0.412)	(0.835)	(0.402)	(0.599)
2nd to 3rd decile	0.233	0.173	0.461	0.979*
	(0.401)	(0.806)	(0.356)	(0.561)
3rd to 4th decile	0.239	0.415	0.464	0.0109
	(0.392)	(0.742)	(0.325)	(0.593)
4th to 5th decile	0.119	0.0997	0.684**	0.681
	(0.384)	(0.735)	(0.308)	(0.476)
5th to 6th decile	-0.0385	-0.242	0.424	0.173
	(0.371)	(0.671)	(0.296)	(0.446)
6th to 7th decile	-0.238	-0.277	0.200	0.255
	(0.357)	(0.692)	(0.275)	(0.396)
7th to 8th decile	0.0419	-0.236	0.256	0.321
	(0.353)	(0.611)	(0.260)	(0.336)
8th to 9th decile	-0.150	0.428	0.252	-0.00547
	(0.314)	(0.581)	(0.218)	(0.278)
above 9th decile (reference)	—	—	—	—
Tenure				
less than 2 years	0.389**	0.168	-0.233	-0.204
	(0.175)	(0.401)	(0.218)	(0.372)
2-5 years	0.155	-0.155	-0.0754	-0.168
	(0.151)	(0.338)	(0.189)	(0.359)
5-10 years	0.0514	0.204	-0.220	0.0839
	(0.126)	(0.316)	(0.151)	(0.283)
more than 10 years (reference)	—	—	—	—
Full-time (1/0)	-0.340**	-0.892***	-0.363	-0.784**
	(0.152)	(0.329)	(0.261)	(0.379)
Fixed-term contract (1/0)	0.0577	-0.111	-0.0467	0.283
	(0.143)	(0.343)	(0.183)	(0.293)
Public service sector (1/0)	0.0403	0.240	0.326*	0.423
	(0.173)	(0.399)	(0.196)	(0.331)
Occupation				
Untrained worker (reference)	—	—	—	—
Trained worker	-0.0863	0.525	-0.128	-0.612
	(0.171)	(0.526)	(0.248)	(0.376)
Foreman, highly trained, managerial duties	0.0726	0.397	0.176	-0.234
	(0.231)	(0.621)	(0.297)	(0.460)

Table A.2 continued: Dynamic Multinomial logit model with random effects for second job states

	Women		Men	
	Marginal	***Non-marginal***	***Marginal***	***Non-marginal***
Industry				
Agriculture, energy, mining	0.783	-20.27***	0.555	-0.362
	(0.749)	(1.285)	(0.574)	(0.741)
Manufacturing	0.260	0.985	1.042**	0.0554
	(0.374)	(0.815)	(0.468)	(0.689)
Construction	0.424	5.105***	0.584	-0.0617
	(0.517)	(1.309)	(0.521)	(0.777)
Services	0.162	0.622	0.758*	-0.536
	(0.366)	(0.716)	(0.452)	(0.705)
Firmsize				
less than 20 employees (reference)	—	—	—	—
20 to 199 employees	0.144	-0.554	0.212	0.0874
	(0.161)	(0.424)	(0.219)	(0.347)
200 and more employees	0.0377	-0.599	0.0891	0.0359
	(0.169)	(0.476)	(0.260)	(0.360)
Worker characteristics				
Family status				
Single and no children (reference)	—	—	—	—
Partner and no children	-0.315	-0.235	-0.0709	-0.0454
	(0.192)	(0.357)	(0.230)	(0.360)
Partner and children	-0.233	-0.574	-0.0261	-0.447
	(0.218)	(0.455)	(0.233)	(0.362)
Single and children	-0.0965	-0.205	-0.398	-1.343**
	(0.220)	(0.525)	(0.514)	(0.559)
Preferred working hours first job				
More hours	0.234**	-0.187	0.103	0.175
	(0.0928)	(0.219)	(0.111)	(0.172)
Same hours (reference)	—	—	—	—
Less hours	0.0528	0.323	-0.0573	-0.0220
	(0.103)	(0.220)	(0.106)	(0.175)
Employment status partner				
Not working (reference)	—	—	—	—
Full time	-0.246*	-0.259	-0.278	-0.0513
	(0.142)	(0.283)	(0.175)	(0.273)
Part time	-0.183	-0.0581	0.0481	-0.0693
	(0.281)	(0.630)	(0.151)	(0.210)
Other	0.107	0.736	0.234	-0.246
	(0.401)	(1.204)	(0.193)	(0.290)
Age				
18-25 years old	0.366	-1.415	0.550	0.756
	(0.432)	(1.396)	(0.505)	(1.226)
26-35 years old	0.215	-0.671	0.190	-0.315
	(0.300)	(0.708)	(0.335)	(0.549)
36-45 years old	-0.0219	-0.172	0.0587	0.501
	(0.224)	(0.541)	(0.246)	(0.402)
46-55 years old	0.0935	0.0897	0.150	0.287
	(0.160)	(0.394)	(0.184)	(0.262)
older than 55 years (reference)	—	—	—	—

Table A.2 continued: Dynamic Multinomial logit model with random effects for second job states

	Women		Men	
	Marginal	***Non-marginal***	***Marginal***	***Non-marginal***
Skill level				
Low skill	2.183**	-1.211	-1.291	-2.836**
	(0.992)	(1.842)	(1.115)	(1.327)
Medium skill (reference)	—	—	—	—
High skill	1.008	1.965*	-0.159	1.279*
	(0.800)	(1.021)	(0.608)	(0.736)
Lives in East Germany (1/0)	0.0166	-3.525***	-2.365***	-0.899
	(0.694)	(0.965)	(0.854)	(0.667)
Migration Background				
No migration background (reference)	—	—	—	—
Direct migration background	0.145	0.0931	0.214	-0.435
	(0.129)	(0.338)	(0.163)	(0.309)
Indirect migration background	0.0434	-0.165	-0.0838	-0.919**
	(0.190)	(0.500)	(0.246)	(0.466)
Year				
2004 (reference)	—	—	—	—
2005	0.330	-0.177	0.430	0.310
	(0.267)	(0.506)	(0.269)	(0.367)
2006	0.140	-0.364	0.152	0.297
	(0.278)	(0.553)	(0.303)	(0.437)
2007	0.193	-0.676	0.440	0.657
	(0.280)	(0.556)	(0.297)	(0.416)
2008	0.318	-0.192	0.255	0.548
	(0.282)	(0.531)	(0.306)	(0.431)
2009	0.494*	-0.158	0.310	0.582
	(0.283)	(0.559)	(0.300)	(0.447)
2010	0.209	-0.449	0.00409	0.440
	(0.283)	(0.539)	(0.307)	(0.439)
2011	0.337	-0.893	0.524*	0.881**
	(0.290)	(0.579)	(0.312)	(0.424)
2012	0.350	-1.146**	0.349	0.608
	(0.287)	(0.569)	(0.306)	(0.452)
2013	0.615**	-1.215**	0.334	0.217
	(0.279)	(0.575)	(0.301)	(0.469)
2014	0.524*	-0.883	0.277	0.231
	(0.278)	(0.548)	(0.306)	(0.439)
2015	0.381	-0.705	0.276	0.312
	(0.283)	(0.549)	(0.315)	(0.471)
2016	0.410	-0.673	0.463	0.409
	(0.281)	(0.561)	(0.316)	(0.464)
2017	0.720**	-0.317	0.802**	0.559
	(0.284)	(0.541)	(0.315)	(0.470)
2018	0.779***	-0.444	0.787**	0.839*
	(0.282)	(0.554)	(0.316)	(0.482)
Initial conditions t=0				
Second job status				
Only main job (reference)	—	—	—	—
Marginal second job	2.205***	1.011***	3.163***	2.736***
	(0.165)	(0.333)	(0.197)	(0.308)
Non-marginal second job	1.521***	4.667***	2.063***	5.156***
	(0.324)	(0.668)	(0.273)	(0.452)

Table A.2 continued: Dynamic Multinomial logit model with random effects for second job states

	Women		Men	
	Marginal	***Non-marginal***	***Marginal***	***Non-marginal***
Initial conditions t=0				
Main job characteristics				
Main job monthly gross income				
up to 1st decile	-0.385	0.353	-0.758	-0.952
	(0.549)	(1.194)	(0.541)	(0.791)
1st to 2nd decile	-0.00606	0.631	0.358	-0.408
	(0.534)	(1.142)	(0.428)	(0.665)
2nd to 3rd decile	-0.252	0.530	-0.442	-0.836
	(0.526)	(1.125)	(0.409)	(0.604)
3rd to 4th decile	-0.513	0.411	-0.183	-1.434**
	(0.525)	(1.127)	(0.383)	(0.626)
4th to 5th decile	-0.281	0.557	-0.288	-0.939*
	(0.524)	(1.106)	(0.367)	(0.541)
5th to 6th decile	-0.828	0.589	-0.595*	-1.297**
	(0.517)	(1.095)	(0.352)	(0.543)
6th to 7th decile	-0.679	0.205	-0.531	-0.442
	(0.506)	(1.060)	(0.329)	(0.450)
7th to 8th decile	-0.593	0.477	-0.222	-0.387
	(0.505)	(1.044)	(0.306)	(0.403)
8th to 9th decile	-0.481	0.512	-0.117	0.145
	(0.497)	(1.053)	(0.283)	(0.340)
above 9th decile (reference)	—	—	—	—
Tenure				
less than 2 years	-0.290	0.343	0.0331	0.342
	(0.213)	(0.538)	(0.253)	(0.410)
2-5 years	0.107	0.172	0.244	0.441
	(0.200)	(0.487)	(0.234)	(0.395)
5-10 years	-0.0865	0.180	-0.0829	-0.235
	(0.177)	(0.421)	(0.201)	(0.343)
more than 10 years (reference)	—	—	—	—
Full-time (1/0)	0.234	0.582	0.170	0.625
	(0.162)	(0.360)	(0.298)	(0.454)
Fixed-term contract (1/0)	-0.0856	-0.559**	-0.185	0.215
	(0.107)	(0.272)	(0.133)	(0.207)
Public service sector (1/0)	-0.0671	0.0368	0.217	0.481
	(0.179)	(0.422)	(0.274)	(0.373)
Occupation				
Untrained worker (reference)	—	—	—	—
Trained worker	-0.0633	0.599	-0.188	-0.0109
	(0.193)	(0.432)	(0.337)	(0.571)
Foreman, highly trained, managerial duties	-0.217	0.355	-0.105	-0.437
	(0.270)	(0.569)	(0.403)	(0.673)
Industry				
Agriculture, energy, mining	0.321	1.997	0.473	-0.895
	(0.605)	(1.445)	(0.527)	(0.757)
Manufacturing	0.673**	-0.530	0.0433	-0.551
	(0.286)	(0.711)	(0.277)	(0.438)
Construction	1.873***	2.421**	-0.291	-0.766
	(0.596)	(1.089)	(0.446)	(0.586)
Services	0.306	-0.662	-0.117	-0.589*
Firmsize	(0.219)	(0.439)	(0.255)	(0.353)
less than 20 employees (reference)	—	—	—	—
20 to 199 employees	-0.0300	0.302	0.0912	0.0366
	(0.177)	(0.409)	(0.246)	(0.400)
200 and more employees	-0.00904	0.145	0.0932	0.302
	(0.186)	(0.421)	(0.262)	(0.423)

Table A.2 continued: Dynamic Multinomial logit model with random effects for second job states

	Women		**Men**	
	Marginal	***Non-marginal***	***Marginal***	***Non-marginal***
Initial conditions t=0				
Worker characteristics				
Family status				
Single and no children (reference)	—	—	—	—
Partner and no children	0.0762	-0.465	-0.348	-0.198
	(0.217)	(0.476)	(0.251)	(0.411)
Partner and children	0.326	-0.144	0.124	0.244
	(0.232)	(0.519)	(0.247)	(0.394)
Single and children	0.360	0.184	-0.285	-0.907
	(0.235)	(0.503)	(0.527)	(1.035)
Preferred working hours first job				
More hours	-0.0608	-0.144	-0.157	0.00172
	(0.117)	(0.269)	(0.146)	(0.223)
Same hours (reference)	—	—	—	—
Less hours	0.205*	0.0398	0.0812	0.0442
	(0.124)	(0.281)	(0.151)	(0.255)
Employment status partner				
Not working (reference)	—	—	—	—
Full time	-0.0307	0.0136	0.288	-0.344
	(0.149)	(0.331)	(0.225)	(0.326)
Part time	0.456	-0.187	0.217	-0.377
	(0.391)	(0.963)	(0.197)	(0.314)
Other	-0.0153	0.886	0.830***	-0.775*
	(0.648)	(1.488)	(0.275)	(0.466)
Age				
18-25 years old	0.520	1.359	0.850	-0.138
	(0.515)	(1.148)	(0.621)	(1.038)
26-35 years old	0.414	1.091	0.627	0.103
	(0.425)	(0.950)	(0.487)	(0.750)
36-45 years old	0.229	0.883	0.236	-0.0910
	(0.360)	(0.752)	(0.404)	(0.611)
46-55 years old	0.0248	0.550	-0.225	-0.186
	(0.283)	(0.580)	(0.293)	(0.435)
older than 55 years (reference)	—	—	—	—
Skill level				
Low skill	0.490	-0.971	-1.754*	-2.532*
	(0.742)	(1.294)	(0.924)	(1.521)
Medium skill (reference)	—	—	—	—
High skill	0.168	-1.487	-1.182*	-0.457
	(0.693)	(1.058)	(0.612)	(1.140)
Lives in East Germany (1/0)	0.170	0.00771	-0.156	-0.640
	(0.484)	(0.800)	(0.543)	(0.710)
Migration Background				
No migration background (reference)	—	—	—	—
Direct migration background	0.0124	0.00527	0.0286	0.0461
	(0.471)	(0.604)	(0.553)	(0.513)
Indirect migration background	0.0302	0.00293	0.0108	0.00974
	(0.285)	(0.0258)	(0.347)	(0.0946)

Table A.2 continued: Dynamic Multinomial logit model with random effects for second job states

	Women		Men	
	Marginal	***Non-marginal***	***Marginal***	***Non-marginal***
Average of time-varying variables				
Main job characteristics				
Main job monthly gross income				
up to 1st decile	0.0896	-1.111	-1.239	-1.832
	(0.726)	(1.628)	(0.955)	(1.553)
1st to 2nd decile	-0.284	-0.996	-0.396	-2.256*
	(0.695)	(1.509)	(0.739)	(1.255)
2nd to 3rd decile	0.0417	-0.458	0.106	-1.030
	(0.684)	(1.443)	(0.673)	(1.094)
3rd to 4th decile	0.218	-0.470	0.111	-0.269
	(0.686)	(1.449)	(0.621)	(1.063)
4th to 5th decile	-0.130	0.00495	0.0188	-0.491
	(0.674)	(1.394)	(0.570)	(0.888)
5th to 6th decile	0.526	0.442	0.548	-0.336
	(0.670)	(1.359)	(0.557)	(0.834)
6th to 7th decile	1.142*	-0.0461	0.356	-0.0248
	(0.629)	(1.358)	(0.515)	(0.736)
7th to 8th decile	-0.0579	0.558	0.263	-0.915
	(0.629)	(1.199)	(0.478)	(0.656)
8th to 9th decile	0.632	0.238	-0.382	-1.074*
	(0.612)	(1.307)	(0.430)	(0.593)
above 9th decile	—	—	—	—
Tenure				
less than 2 years	0.437	0.485	0.221	0.0917
	(0.336)	(0.842)	(0.411)	(0.687)
2-5 years	0.380	1.147	-0.398	0.683
	(0.308)	(0.703)	(0.391)	(0.680)
5-10 years	0.454	0.127	0.289	-0.108
	(0.291)	(0.676)	(0.358)	(0.653)
more than 10 years	—	—	—	—
Full-time (1/0)	-0.155	0.110	-0.548	-1.014
	(0.269)	(0.571)	(0.472)	(0.724)
Fixed-term contract (1/0)	0.0200	0.622	-0.00153	0.317
	(0.268)	(0.678)	(0.301)	(0.488)
Public service sector (1/0)	-0.0417	-0.401	-0.0389	-0.393
	(0.281)	(0.714)	(0.373)	(0.550)
Occupation				
Untrained worker	3.488	2.557	-2.067	9.094
	(5.385)	(6.934)	(4.033)	(7.771)
Trained worker	3.402	1.214	-1.847	10.32
	(5.370)	(6.903)	(4.000)	(7.749)
Foreman, highly trained, managerial duties	3.732	2.612	-2.074	10.72
	(5.380)	(6.949)	(4.006)	(7.727)
Industry				
Agriculture, energy, mining	-1.179	-1.178	-1.187	2.447
	(1.144)	(2.636)	(1.013)	(1.623)
Manufacturing	-0.955	-0.842	-0.0508	1.383
	(0.655)	(1.637)	(0.775)	(1.443)
Construction	-1.640*	-21.96***	0.338	1.923
	(0.975)	(3.248)	(0.888)	(1.574)
Services	-0.244	0.345	0.631	2.638*
	(0.607)	(1.357)	(0.757)	(1.433)

Table A.2 continued: Dynamic Multinomial logit model with random effects for second job states

	Women		Men	
	Marginal	***Non-marginal***	***Marginal***	***Non-marginal***
Average of time-varying variables				
Main job characteristics				
Firmsize				
less than 20 employees	0.239	-0.120	0.618	0.750
	(0.297)	(0.724)	(0.423)	(0.632)
20 to 199 employees	0.0149	-0.413	0.0537	0.375
	(0.247)	(0.538)	(0.287)	(0.468)
200 and more employees	—	—	—	—
Worker characteristics				
Family status				
Single and no children	0.362	-0.453	-0.575	-3.337**
	(0.379)	(0.834)	(0.913)	(1.517)
Partner and no children	0.510	0.792	-0.299	-2.836*
	(0.410)	(0.849)	(0.954)	(1.550)
Partner and children	0.169	0.964	-0.764	-2.678*
	(0.389)	(0.819)	(0.956)	(1.574)
Single and children	—	—	—	—
Preferred working hours first job				
More hours	-0.223	0.130	-0.916*	-1.285*
	(0.452)	(0.983)	(0.495)	(0.712)
Same hours	-1.120**	-1.640*	-1.434***	-1.311*
	(0.456)	(0.978)	(0.492)	(0.702)
Less hours	-0.967**	-0.762	-1.510***	-1.893***
	(0.438)	(0.942)	(0.481)	(0.685)
Employment status partner				
Not working	-0.637	2.857	0.251	-1.196
	(1.049)	(2.816)	(0.447)	(0.728)
Full time	-0.742	2.317	0.430	-0.932
	(1.049)	(2.838)	(0.495)	(0.770)
Part time	-0.549	1.849	0.133	-1.015
	(1.133)	(3.187)	(0.469)	(0.725)
Other	—	—	—	—
Age				
18-25 years old	-0.808	0.0453	-0.798	-1.082
	(0.767)	(2.087)	(0.915)	(2.051)
26-35 years old	-0.0866	0.0280	-0.349	0.0407
	(0.547)	(1.319)	(0.629)	(1.028)
36-45 years old	0.136	0.0271	-0.0443	-0.626
	(0.429)	(0.946)	(0.496)	(0.790)
46-55 years old	0.288	0.212	-0.0424	-0.837
	(0.327)	(0.704)	(0.370)	(0.609)
older than 55 years	—	—	—	—
Skill level				
Low skill	-1.638	1.737	1.500	6.284***
	(1.220)	(2.313)	(1.370)	(1.578)
Medium skill	1.414	0.487	-1.178	1.052
	(1.142)	(1.576)	(0.952)	(1.556)
High skill	—	—	—	—
Lives in East Germany (1/0)	-0.658	3.220***	1.976**	1.230
	(0.929)	(1.129)	(0.942)	(1.202)

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