FRIEDRICH-ALEXANDER-UNIVERSITÄT ERLANGEN-NÜRNBERG

Lehrstuhl für VWL, insbes. Arbeitsmarkt- und Regionalpolitik
Professor Dr. Claus Schnabel

Diskussionspapiere
Discussion Papers

NO. 116

Does it Pay to Go Public? Understanding the Public-Private Sector Wage Gap in Germany

MARINA BONACCOLTO-TÖPFER, CAROLINA CASTAGNETTI AND STEPHANIE PRÜMER

MARCH 2021

ISSN 1615-5831

Editor: Prof. Dr. Claus Schnabel, Friedrich-Alexander-Universität Erlangen-Nürnberg

Does it Pay to Go Public?
Understanding the Public-Private Sector Wage Gap in Germany*

Marina Bonaccolto-Töpfer[†] Carolina Castagnetti[‡] Stephanie Prümer[§]

Abstract: Using data from the German Socio-Economic Panel 1984-2017, this paper provides first evidence on the public-private sector wage gap in Germany based on a fixed effect quantile approach. The results reveal substantial differences in the decomposition of the gap compared to the standard cross-sectional approach. We find that women earn more in public employment, while men are penalized. Our analysis suggests that this penalization is not related to compensating wage differentials. Against the background of demographic change, the public sector may face difficulties to recruit (skilled) men and may need to adjust its pay schemes to fair and merit-based ones.

Zusammenfassung: Mit Daten des Sozioökonomischen Panels 1984-2017 untersucht dieser Beitrag die Lohnlücke zwischen dem öffentlichen und privaten Sektor in Deutschland und liefert dabei erste Evidenz, die auf einem Quantilsansatz mit fixen Effekten beruht. Mit diesem Ansatz finden wir substantielle Unterschiede in der Zerlegung der Lohnlücke im Vergleich zum Standard-Querschnittsansatz. Demnach verdienen Frauen im öffentlichen Sektor mehr, während Männer benachteiligt werden. Unsere Analyse legt nahe, dass diese Benachteiligung nicht mir kompensierenden Lohndifferentialen zusammenhängt. Vor dem Hintergrund des demografischen Wandels könnte der öffentliche Sektor daher Probleme haben, (qualifizierte) Männer zu rekrutieren, und sollte seine Entlohnungssysteme fair und leistungsorientiert gestalten.

Keywords: Public-Private Sector Wage Gap, Quantile Regression for Panel Data, Germany

JEL Codes: J31, J45, C33

*For helpful comments and suggestions, we thank Boris Hirsch, Luisa Rosti, Claus Schnabel and participants of the 29th BGPE Research Workshop and seminars at the University of Erlangen-Nürnberg.

[†] University of Erlangen-Nürnberg

[‡] University of Pavia

[§] University of Erlangen-Nürnberg, correspondence to: University of Erlangen-Nürnberg, School of Business, Economics and Society, Chair of Labor and Regional Economics, Lange Gasse 20, 90403 Nuremberg. E-mail: stephanie.pruemer@fau.de

1 Introduction

Demographic change represents a major challenge for the German labor market. The working-age population in Germany is expected to shrink by 30% between 2013 and 2060 (Federal Statistical Office, 2015). Moreover, in order to counterbalance skilled labor shortages that are accelerated by the aging society in Germany, the government adopted the Skilled Labour Concept in 2011 (Gramke et al., 2012). Demographic change in combination with skill shortages challenges particularly the public sector since its employees are on average older and better educated than employees in the private sector (Dustmann and van Soest, 1998; Melly, 2005). As a consequence, the public sector will need to replace a significant share of its workforce in the not-to-far future and to compete for employees with the private sector. A premise to tackle these challenges is attractive and fair remuneration. Indeed, remuneration matters for both public- and private-sector recruitment making the composition of the Public-Private Sector Wage Gap (PPWG) an important policy issue.

This paper revisits the PPWG in Germany. We estimate and decompose the gap in Germany using a Fixed Effect (FE) quantile approach. This approach allows us to take the panel dimension of the data into account. The latter is generally neglected in the analysis of the PPWG across the distribution (exceptions are Bargain et al., 2018; Castagnetti and Giorgetti, 2019; Hospido and Moral-Benito, 2016, for France, Spain and Italy, respectively). In order to show that the decomposition results may change substantially when taking the panel dimension of the data into account, we start by presenting the standard pooled sample approach (based on cross-sectional data). Next, we compare the results of this pooled sample approach with those of the FE approach. As sorting in public- or private-sector employment differs by gender (Pfeifer, 2011), we conduct the analysis separately for men and women.[1]

We use data from the German Socio-Economic Panel (SOEP) for the years 1984-2017. This data set is particularly suited for analyzing the PPWG with a FE approach due to its long time horizon. Additionally, by using SOEP data we are in line with previous studies for Germany (Dustmann and van Soest, 1997, 1998; Jürges, 2002; Melly, 2005).

Dustmann and van Soest (1997, 1998) were the first to consider the PPWG in Germany. Using switching-regression models, they found that public-sector employees have

[1] Note, however, that by applying a FEs approach we account for individual-specific time-invariant endogenous selection (Hospido and Moral-Benito, 2016).

a comparative wage advantage. Further, conditional on socio-economic variables, wages were on average lower in the public sector for men and higher for women (Dustmann and van Soest, 1998). Jürges (2002) focused on the question how public-sector wage premia are allocated along the wage distribution. His results suggested that the PPWG decreases along the wage distribution. Men experienced wage premia at the lower tail of the wage distribution and wage penalties at the upper tail. In contrast, women earned more in the public sector independent of their rank in the wage distribution. Melly (2005) used standard cross-sectional quantile decomposition to look at the PPWG along the wage distribution. He found that the conditional distribution of wages was more compressed in the public sector. Moreover, inequalities between individuals with comparable education or experience were lower in the public sector. The latter resulted in a smaller gender pay gap in the public sector.

We contribute to the literature in three ways. First, we revisit the PPWG in Germany relying on standard and well-established methods to estimate and decompose the PPWG (e.g., Machado and Mata, 2005). Second, we are the first to estimate and decompose the German PPWG using the FE quantile approach proposed by Castagnetti and Giorgetti (2019). The approach offers several advantages compared to similar studies (e.g., Bargain et al., 2018). In particular, the approach is flexible as it allows for parameter heterogeneity by estimating separate wage equations for the two sectors. That is, we do not not rely on movers between the public and private sector (or vice versa) for identification. Third, as Incidental Parameter Bias (IPB) represents a major problem in panel data estimation with the number of observations $N \to \infty$ and fixed time periods T, we correct the public-sector wage premium along the distribution for this bias. To be precise, we use the recentered half-panel jackknife-correction proposed by Dhaene and Jochmans (2015) and Bargain et al. (2018).

We find that the PPWG changes substantially when taking the panel dimension of the data into account. This result holds for both men and women. Women benefit from public-sector employment at all points of the wage distribution, while men are generally better endowed in the public sector (positive characteristics effect) without being remunerated accordingly (negative coefficients effect). This finding implies that the public sector may be successful in recruiting women but may fail to recruit men. Further, in order to investigate whether the negative coefficients effect may be attributable to compensating wage differentials, we exclude the subgroup of civil servants from the analysis. This subgroup enjoys special privileges such as job stability and is predominant in public employment. The results suggest that compensating wage differentials do not play a major role in explaining the PPWG in Germany.

The remainder of this paper proceeds as follows. In Section 2, we outline our empirical strategy. Section 3 presents the data set as well as descriptive statistics, while Section 4 shows the results of our empirical analysis. In Section 5, we present the IPB corrected wage premium along the distribution before looking at the evolution of the PPWG over time in Section 6. In Section 7, we repeat the analysis without the subgroup of civil servants for robustness. Finally, Section 8 concludes.

2 Empirical strategy

In this Section, we present our empirical strategy. First, we outline the estimation model for the cross-sectional approach. That is, the approach that does not consider the panel structure of the data. Second, we describe the FE quantile approach. As stated, the procedure is run separately for men and women as sorting of men and women in public employment may differ. Endogenous sorting into public employment may play a role as well. However, we control for individual-specific time-invariant endogenous selection by using a FEs approach (Dustmann and Rochina-Barrachina, 2007; Hospido and Moral-Benito, 2016).

We use quantile regression to estimate the wage equation (Koenker and Bassett, 1978). In case of the cross-sectional approach, we pool the different survey waves of our data. This procedure is in line with e.g., Melly (2005). For the pooled sample, we assume a linear specification and estimate the following model for individual i with $i \in 1, \ldots, N$:

$$\begin{aligned} Q_\theta(y_i|x_i) &= x_i\beta_\theta \\ y_i &= x_i\beta_\theta + u_{\theta i} \end{aligned} \tag{1}$$

where $Q_\theta(y_i|x_i)$ is the conditional quantile at θ of the dependent variable y (log hourly wages), given the covariates x (individual characteristics). The distribution of the error term $u_{\theta i}$ is left unspecified and we assume that $Q_\theta(u_{\theta i}|x_i) = 0$. In analogy to mean regressions (standard OLS), the coefficients in (1) can be interpreted as the effect of x at the θth conditional quantile of y given x (conditional mean interpretation, Fortin et al., 2011).

We estimate this model separately for men and women in the public and private sector, respectively, at different quantiles, with $\theta = 0.1, 0.2, \ldots, 0.9$. In case of (conditional) quantile regressions, the explanatory variables, i.e. individual observable characteristics, are allowed to affect the various quantiles differently. Therefore, we can control for differences in observable characteristics between wages of public- and private-sector employees.

2.1 Decomposition along the wage distribution

The above mentioned analogy in the interpretation of quantile and standard (mean) regressions is not transferable to decomposition methods (Fortin et al., 2011). Using quantile regressions, we cannot decompose quantiles in the same way we decompose the mean using standard (mean) regressions. While both unconditional and conditional mean interpretations are valid in case of standard (mean) regressions, only the conditional mean interpretation is applicable in case of quantile regressions (Fortin et al., 2011; Machado and Mata, 2005). The reason is that the law of iterated expectations does not apply in the case of quantiles.

We use the Machado and Mata (2005) decomposition in order to decompose the PPWG in a characteristics (explained) and a coefficients (unexplained) component (aggregate decomposition). This procedure allows us to obtain Oaxaca-Blinder-type decompositions of the unconditional distribution of y. The Machado and Mata (2005) decomposition approach estimates in a first step quantile regressions as a way of characterizing the full conditional distribution of y given x. The second step involves estimating the marginal density function of wages by simulating a sample from the (estimated) conditional distribution (see Machado and Mata, 2005, for details). The estimates are then used to construct the different components of the aggregate decomposition.

This method allows us to interpret the estimated coefficients as the effect of increasing the mean value of x on the unconditional quantile Q_θ (unconditional mean interpretation). By using the decomposition approach of Machado and Mata (2005), a major drawback of (conditional) quantile regressions – that only the conditional mean interpretation is valid – can thus be avoided.

In case of the PPWG, we construct a counterfactual distribution of y_C^{Pub}, i.e. a distribution of public-sector wages had the wage structure been the same as in the private sector. We do so by drawing random samples θ_m^*, $m = 1, 2, \ldots, 5000$ from a uniform distribution $U[0, 1]$. We have k observations with $k \in Pub, Priv$ and samples $(y_j^k, x_j^k) : j = 1, \ldots, N_k$ for all populations k such that we can estimate $Q_\theta(y_j^k|x_j^k)$ separately for the two groups. Pub identifies public- and $Priv$ private-sector employees. For each θ_m, we estimate $\beta^k(\theta)$ for each sample k as:

$$\hat{\beta}_{\theta_m^*} = \arg\min_{\beta} \sum_{j=1}^{N_k} \rho_{\theta_i^*}(y_j^k - x_j^k \beta_\theta) \tag{2}$$

where $\rho_\theta(u) = u(\theta - 1(u < 0))$ denotes the quantile loss function and $k = Pub, Priv$.

Next, we randomly draw 5,000 public-sector employees with replacement and use their characteristics (x^{*Pub}) to predict wages using the estimated coefficients $\beta^{Priv}(\theta)$ and generate a set of predicted wages $\hat{y}_C^{Pub} = x^{*Pub}\hat{\beta}^{Priv}(\theta)$. The latter represents the estimated counterfactual distribution, i.e. what public-sector employees would have earned if they were paid like private-sector employees. We compare then the counterfactual distribution with the empirical public- and private-sector distributions $\hat{y}^k(\theta) = x^k\hat{\beta}^k(\theta)$. The resulting decomposition reads then as:

$$y^{Pub}(\theta) - y^{Priv}(\theta) = \underbrace{[\hat{y}^{Pub}(\theta) - \hat{y}_C^{Pub}(\theta)]}_{\text{coefficients effect}} + \underbrace{[\hat{y}_C^{Pub}(\theta) - \hat{y}^{Priv}(\theta)]}_{\text{characteristics effect}} + \text{residual} \tag{3}$$

where $y^k(\theta)$ is the observed log hourly wage for $k = Pub, Priv$. $\hat{y}^k(\theta)$ represents the estimate of log hourly wages for k based on the observed sample and $\hat{y}_C^{Pub}(\theta)$ is the estimated counterfactual log hourly wage. The first term is the coefficients effect, while the second term represents the characteristics effect. The residual term captures the changes unaccounted for by the estimation model and is generally negligible (e.g., Castagnetti and Giorgetti, 2019; Melly, 2005). If not indicated differently, the standard errors are estimated using the procedure proposed by Chernozhukov et al. (2013).

The pooled sample approach allows us to gain insights on how the PPWG and its components in Germany change along the wage distribution. However, this approach neglects the panel dimension of the data. As stated, we overcome this shortcoming by using a FE quantile approach that we outline in the next Subsection.

2.2 Fixed effect quantile approach

In order to account for unobserved time-constant individual heterogeneity, we estimate the following FE quantile regression model at quantile θ for individual i at time t:

$$Q_\theta(y_{it}|x_{it}) = \alpha_i + x_{it}\beta_\theta \tag{4}$$

$$y_{it} = x_{it}\beta_\theta + u_{\theta it} \tag{5}$$

where y_{it} denotes the log hourly wage, α_i denotes the individual FE and x_{it} represents the set of covariates with $i = 1, \ldots, N$ individuals and $t = 1, \ldots, T$ time periods.

The FE quantile regression model controls for individual-specific heterogeneity, while exploring heterogeneous covariate effects providing a more flexible method for analyzing panel data than the pooled sample approach. Yet, FE quantile regression faces several challenges. First, the method of differencing out the FEs used for the conditional linear mean model is not applicable in case of conditional quantiles. Second, the objective function cannot be differentiated. The implication is that standard asymptotic analyses of panel data models are not directly applicable to quantile regression.

In equation (4), we assume a pure location shift effect for the individual parameters; i.e. the FEs affect all quantiles in the same way. We follow the approach of Canay (2011) to estimate equation (4). This approach is a two-step estimator that first estimates the individual FEs by traditional mean estimation (e.g., estimation in first differences or by means of the within estimator). In a second step, it estimates corrected wages on the covariates x_{it} by means of traditional quantile regression. A main advantage of the method of Canay (2011) is that it does not add computational complexity to the model estimation. In fact, estimation and inference that alternative FE quantile regressions use may be hard to conduct when the number of FEs is large. In these cases, point estimates are difficult to recover, and the computation of the variance-covariance matrix based on the limiting distribution becomes impracticable. In addition, inference using FE quantile regressions is difficult to conduct in practice. We rely on the good finite-sample properties of Canay (2011)'s estimator that hold even for small values of T. We can rely on $T = 34$ and Canay (2011) showed that the two-step estimator performs already pretty well when $T = 20$.

As in case of the pooled sample approach, we make use of the Machado-Mata algorithm to decompose the PPWG. However, in case of the FE approach, we decompose the gap based on corrected wages. Doing so allows us to account for both individual permanent heterogeneity and to decompose the PPWG along the distribution in a characteristics and coefficients part (Castagnetti and Giorgetti, 2019). Observe that in order to decompose the PPWG along the wage distribution and to take the panel dimension of the data into account, we add a further step to the approach of Canay (2011).

In the following, we outline the steps in detail. First, we estimate FE quantile regressions using the approach of Canay (2011), i.e. we estimate the individual FE $\hat{\alpha}_i$ using FE regression for the public and private sector respectively:

$$y_{it}^k = \alpha_i^k + x_{it}^k \beta_\theta^k + \epsilon_{\theta it}^k \tag{6}$$

where $k = Pub, Priv$. Second, we estimate the following model based on corrected wages separately for the two sectors k:

$$Q_\theta(\tilde{y}_{it}^k | x_{it}) = x_{it}^k \beta_\theta^k \tag{7}$$

where $\tilde{y}_{it} = y_{it} - \hat{\alpha}_i$ is the log hourly wage net of the individual time-constant heterogeneity or the individual FE (corrected wage). Third, we decompose the PPWG as in equation (3), but based on $\tilde{y}^k_{it}$, using the approach of Machado and Mata (2005) explained above.

To sum up, an advantage of the approach is that it allows us to apply an intuitive decomposition. That is, it corresponds to the logic of the Oaxaca-Blinder method decomposing the PPWG in a coefficients and characteristics effect. Moreover, we estimate separate wage equations for the two sectors allowing for parameter heterogeneity, while similar studies (e.g., Bargain et al., 2018), identified the PPWG by means of a dummy variable only. Further, the interpretation of the public-sector parameter coefficient is partly misleading in Bargain et al. (2018). The authors claim that the variation of this coefficient over the distribution captures differences over time in the public sector. That is, it captures periods of high wages in the public compared to the private sector. However, the latter is true only if transitions from public to private employment (and vice versa) are independent of any upgrade in the job position. Our approach allows us to circumvent these problems, as it does not rely on movers between the public and private sector (or vice versa) for identification.

One of the main issues of FE quantile regression is the IPB. To be precise, it is a general problem of nonlinear models estimated on panel data. IPB leads to inconsistent estimates when the number of individual-year observations goes to infinity, while the number of time periods is fixed (Neyman and Scott, 1948). In order to account for this bias, we present in Section 5 the corrected public-sector wage premium using a recentered half-panel jackknife correction.

3 Data and descriptive statistics

We use data from the German SOEP over the period 1984-2017. As East Germany is part of the survey only since German re-unification in 1990 and as the integration of the East into the West German public sector after the end of Communism took some time, we exclude East Germany. We consider German part- and full-time employees aged 18-64 years and we restrict the sample to individuals observed at least four times. In total, we observe 12,800 individuals (6,887 men and 5,913 women) on average at least seven times.

As the sample includes only wage earners, the results must be interpreted conditional on the selected sample. As stated, endogenous sorting into public employment may be relevant. The latter may be nonrandom and different for men and women, for instance due to better work-family balance in the public sector that may be particularly relevant for women.

Table 1 presents descriptive statistics of selected controls by sector for men (Panel (a)) and women (Panel (b)).[2] For men, we do not observe a statistically significant raw PPWG at the mean. Further, male public-sector employees outperform their private-sector colleagues in terms of schooling, labor market experience and job tenure. Men in the public sector are on average older and are more often part-time employed but have less often a permanent contract. These descriptive findings on the prevalence of permanent contracts in the German public sector are in line with the literature (Hohendanner et al., 2015; Prümer and Schnabel, 2019). Male public-sector employees are more often married and work more often in larger firms. The latter is a typical characteristic of the public sector (Ellguth and Kohaut, 2011; Gregory and Borland, 1999; Prümer and Schnabel, 2019).

Table 1, Panel (b), shows that female public-sector employees earn on average 16% (log approximation) more than their private-sector counterparts. Women in the public sector are also better educated, older, have more years of job tenure, work more often part-time, in larger firms and are more often married compared to women in the private sector. As their male colleagues, female public-sector employees have less often a permanent contract. Yet, in contrast to their male colleagues, women in the public sector do not have statistically significantly more years of labor market experience.

Figure 1 shows descriptively public-private sector differences in wages along the distribution for men and women.[3] Panel (a) of Figure 1 shows that, even though, average male PPWGs or differences in male wages by sector are small and statistically insignificant, this does not hold for the entire distribution. The gap varies substantially across the distribution and is – apart from the very bottom and the 70th percentile – statistically significantly different from zero. This empirical evidence highlights the importance of going beyond the mean when looking at the PPWG. The latter finding holds also for women. Looking at different points of the distribution in Figure 1, Panel (b), we see that women in the public sector earn statistically significantly more than their colleagues in the private sector at lower and middle parts of the distribution, while they earn statistically significantly less at upper parts of the distribution. This increasing pay penalty for both male and female employees may represent a major disadvantage of the public compared to the private sector in the competition for the 'best' employees that represent a scarce resource in times of demographic change. Another reason for the

[2]Panel (a) of Table A.1 in the Appendix shows descriptive statistics for the full sample.
[3]Figure A.1 in the Appendix shows the distribution of log hourly wages by sector.

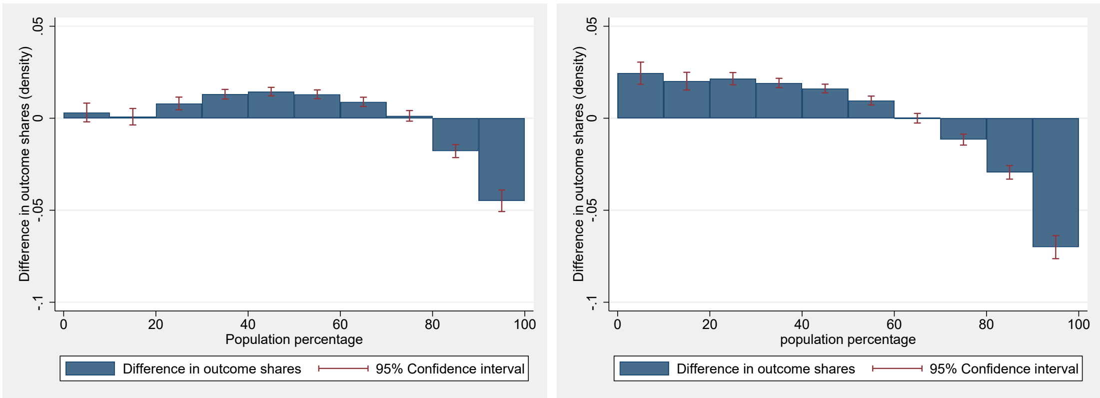
Table 1: Descriptive statistics by sector and gender, selected controls

	(1)	(2)	(3)	(4)	(5)
Sector	Public		Private		
Variable	Mean	Std. dev.	Mean	Std. dev.	Difference
Panel (a): Men					
Log hourly wages	2.707	0.524	2.689	0.550	0.018
Schooling (in years)	13.172	2.935	12.172	2.591	1.000***
Age (in years)	45.047	9.948	42.192	9.999	2.855***
Experience (in years)	21.714	10.638	19.786	10.691	1.928***
Tenure (in years)	17.724	11.08	12.491	10.183	5.233***
Part-time (dummy)	0.053	0.225	0.011	0.104	0.042***
Permanent contract (dummy)	0.71	0.454	0.792	0.406	-0.082***
Medium firm (dummy)	0.308	0.462	0.261	0.439	0.047***
Large firm (dummy)	0.372	0.483	0.242	0.428	0.13***
Married (dummy)	0.74	0.439	0.716	0.451	0.024***
Observations	17,296		47,768		65,064
Panel (b): Women					
Log hourly wages	2.643	0.495	2.48	0.528	0.163***
Schooling (in years)	13.211	2.85	12.182	2.406	1.029***
Age (in years)	44.02	10.048	41.756	10.344	2.264***
Experience (in years)	12.36	9.708	11.966	9.276	0.394
Tenure (in years)	13.373	10.12	9.739	8.725	3.634***
Part-time (dummy)	0.417	0.493	0.35	0.477	0.067***
Permanent contract (dummy)	0.776	0.417	0.808	0.394	-0.032***
Medium firm (dummy)	0.323	0.468	0.224	0.417	0.099***
Large firm (dummy)	0.288	0.453	0.19	0.392	0.098***
Married (dummy)	0.618	0.486	0.565	0.496	0.053***
Observations	19,373		31,315		50,688

Notes: Medium firm equals one if firm has between 200 and 1,999 employees. Large firm equals one if firm has at least 2,000 employees. Reported differences are based on a regression of a public-sector dummy on the selected variables. $*$, $**$ and $***$ denote significance at the 10%-, 5%- and 1%-level, respectively. Robust standard errors (clustered at the individual level) are used. Source: SOEP data v34.

negative PPWG at the top may be that public-sector work is generally not remunerated above formal wage schedules set under collective wage bargaining (Addison et al., 2006; Jung and Schnabel, 2011) and thus faces a top ceiling.

Figure 1: Descriptive statistics of public-private sector differences in wages by gender at selected percentiles



(a) Men

(b) Women

4 Results

The descriptive evidence discussed above suggests that it is important to look at wage gaps along the distribution. We now present the results of our quantile analysis of the PPWG in Germany. In line with Section 2, we start by estimating and decomposing the PPWG in the pooled sample. Next, we account for the panel structure of our data in the estimation and decomposition of the PPWG.

4.1 Pooled sample approach

By means of the Machado-Mata decomposition, we decompose the PPWG in a coefficients and a characteristics effect (see Section 2.1 for details). The intuition of the decomposition is thus similar to the famous Oaxaca-Blinder approach.

Figure 2 shows the PPWG and its decomposition for men (Panel (a)) and women (Panel (b)) in the pooled sample. The male PPWG in the pooled sample is small but positive up to the 80th percentile of the wage distribution and becomes negative thereafter. That is, in the upper tail of the wage distribution men in the public sector face a slight wage penalty. This penalization at the top may be attributed to the fact that public-sector wages are generally subject to collective wage bargaining, while private-sector wages may also lie above formal wage schedules (Jung and Schnabel, 2011). Differences in terms of endowments of public- and private-sector employees – captured in the characteristics effect – are positive but relatively small (less than 5%). The coefficients effect, i.e. the unexplained component of the PPWG, is negative and increasing in absolute terms throughout the distribution. A negative coefficients effect implies that men earn less in the public compared to the private sector despite having similar characteristics. As this effect is generally considered a proxy for discrimination given data constraints (Blau and Kahn, 2017; Briel and Töpfer, 2020; Fortin et al., 2011), top-income men may be prone to leave public for private employment as their endowments, for example in terms of schooling and experience, are not rewarded adequately.[4]

Another explanation for the negative coefficients effect may be compensating wage differentials. In these cases, better working conditions in the public sector – that are mostly unobserved in the data – would explain the negative coefficients effect. The literature generally finds higher job stability in the public sector (Ellguth and Kohaut, 2011; Prümer, 2020). The same holds for employment protection and pension rights of civil servants (Riphahn, 2004). Similarly, better working-time arrangements or better job quality may play a role as well.[5] These positive characteristics of public-sector jobs may compensate men in public-sector employment for lower earnings given identical individual characteristics compared to the private sector. As the coefficients effect is only statistically significantly different from zero from the 65th percentile onwards, the pooled sample approach suggests that only at upper parts of the wage distribution compensating wage differentials may explain a substantial part of the PPWG.

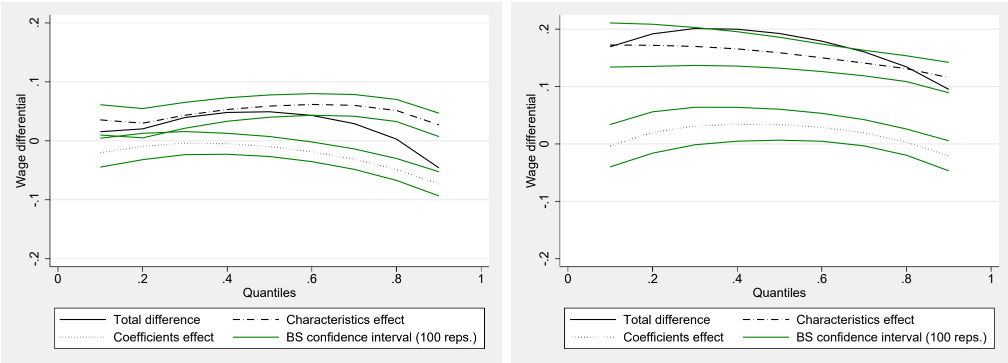
The PPWG for women in the pooled sample is positive throughout the wage distribution and is lowest at the upper tail of the wage distribution (see Figure 2, Panel (b)). Wages for women are therefore higher in the public sector independent of their rank in the wage distribution. Yet, female top-earners gain – relative to their colleagues in the private sector – least from working in the public sector. The overall gap is driven by the characteristics effect, which is positive and relatively stable throughout the wage distribution. The coefficients effect is negligible and statistically not different from zero. Thus, better endowments of female public-sector employees explain the positive PPWG for women throughout the wage distribution. Looking only at the mean would ignore these insights, i.e. that the characteristics effect is the main driver of the PPWG for

[4]The coefficients effect does not account for unobserved characteristics like ability or motivation and does thus not represent an unbiased estimate of discrimination.

[5]Note, however, that Prümer (2020) found evidence for better working-time arrangements but not for better general job quality in the German public sector.

women at all points of the distribution. Observe that, in contrast to their male colleagues, constraints in the public sector to not pay wages above formal wage schedules set under collective wage bargaining are less relevant for females given positive PPWGs throughout the distribution. Similarly, given statistically insignificant or (small) positive coefficients effects, compensating wage differentials attributable to better job characteristics in the public sector do not seem to play a role for women.

Figure 2: PPWG along the wage distribution – pooled sample approach



(a) Men (b) Women

Notes: Variables controlled for in the regressions are: quadratic polynomials of actual labor market experience and age as well as tenure, educational attainment (in years), dummies for holding a permanent contract, a part-time contract, for being employed in a medium (200-1,999 employees) or a large firm (at least 2,000 employees), being married or cohabiting, having a migration background, living in an urban area as well as federal-state, occupation (based on ISCO88 1-Digit) and industry (based on NACE 2-Digits) dummies.

Our results for the pooled sample are partly consistent with existing evidence on the PPWG in Germany by Melly (2005).[6] For women, Melly (2005) found also a positive PPWG and a stable and positive characteristics effect. We find a similar pattern of the male PPWG as Melly (2005), too. Yet, the results of Melly (2005) differ from ours in terms of the size of the PPWG for women along the distribution and the relative influence of the characteristics and coefficients effect on the gap for men.

All in all, our results on the PPWG and its decomposition in the pooled sample suggest that wages of women are higher in the public sector at all points of the wage distribution. Men instead are penalized for working in the public sector in the upper part of the wage distribution. Starting from the 80th percentile men face a slight,

[6] Our results are not directly comparable to earlier studies (e.g., Dustmann and van Soest, 1997, 1998; Jürges, 2002). Although they used SOEP data as well, the methodologies differed. Dustmann and van Soest (1998) estimated switching regression models and did not look at different points of the wage distribution. Additionally, they restricted their analysis to men. Jürges (2002) looked at different points of the wage distribution but used the decomposition approach of Juhn et al. (1993).

though negative, PPWG. The positive PPWG for women in the pooled sample can be attributed to a positive, stable characteristics effect, i.e. to advantages of female public-sector employees in terms of endowments. The male PPWG is driven by the negative coefficients effect at the top. The latter indicates that male public-sector employees are treated differently compared to their private sector counterparts in terms of remuneration at upper parts of the wage distribution. The negative PPWG for male top-earners may be attributed to compensating wage differentials or – as stated – may represent unfair treatment of male top-earners in the public compared to their colleagues in the private sector.

These results based on the pooled sample provide a first insight of how the PPWG changes along the wage distribution. However, so far we have neglected the panel structure of the SOEP. Therefore, in the next subsection, we consider individual time-constant heterogeneity in the estimation.

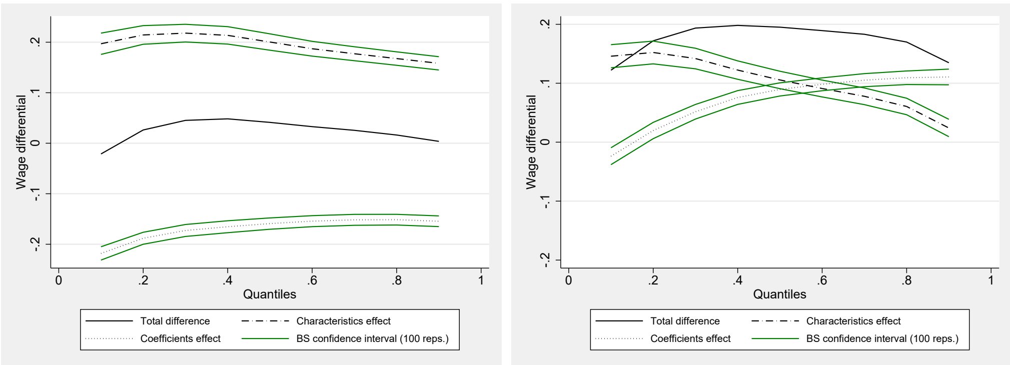
4.2 Fixed effect approach

In this Section, we adopt the three-step procedure for decomposing the PPWG outlined before. First, we estimate the individual FE following Canay (2011). Second, we estimate corrected wages. Third, we decompose the PPWG using the approach of Machado and Mata (2005) with corrected wages as dependent variable.

Figure 3 shows the PPWG by gender applying FE quantile decomposition. For men, the observed PPWG is close to zero throughout the entire wage distribution. That is, we find only a slight difference between male wages in the public and the private sector at all points of the wage distribution (see Figure 3, Panel (a)). We observe a declining and positive characteristics effect as well as a decreasing (in absolute terms) and negative coefficients effect. In sum, both effects counterbalance. Thus, men are better endowed in the public sector (positive characteristics effect) but are penalized in terms of pay for working in the public sector (negative coefficients effect) at all points of the wage distribution. This penalization is highest at the bottom and lowest at the top. Male public-sector employees outperform their private-sector counterparts in terms of endowments particularly at the bottom and relatively less at the top of the wage distribution. That is, the characteristics effect is highest at the bottom and lowest at the top. These findings are in contrast to the decomposition results in the pooled sample, where both the characteristics and the coefficients effect are much smaller in absolute terms. Further, in the pooled sample, the coefficients effect is increasing (in absolute terms), while the characteristics effect is decreasing along the distribution.

The PPWG for women is slightly inverted U-shaped and positive throughout the wage distribution (see Figure 3, Panel (b)). The characteristics effect is positive at all points of the distribution but becomes less important at upper points of the distribution. Thus, women in the public sector are better endowed than their private-sector counterparts throughout. This difference is most pronounced at the lower end of the distribution. While the characteristics effect dominates at lower parts, the coefficients effect dominates at the upper part of the distribution. Sector differences in remuneration, starting from negative values at the bottom, strictly increase towards higher percentiles. Finally, at the upper tail of the distribution the coefficients effect is dominant. In contrast to the findings from the pooled sample, the coefficients effect now contributes to the total PPWG for women.

Figure 3: PPWG along the wage distribution accounting for FE



(a) Men (b) Women

Notes: Variables controlled for in the regressions are the same as in the pooled sample. Note, however, that all time-constant heterogeneity at the individual level is dropped automatically.

Exploiting the panel structure of our data leads to new insights on the PPWG in Germany for both, men and women. Women benefit from being in the public sector, what may contribute to a high appeal of public-sector employment for women in general. Compensating wage differentials do not seem to play a role for women, as the PPWG – and especially the coefficients effect – is positive throughout the wage distribution (except the very bottom of the distribution).

For men, we find only a small PPWG due to a counterbalancing effect of the characteristics and the coefficients effect. At a first glance, this small total gap may be interpreted as equal opportunities between the public and private sector. The decomposition analysis, however, shows that this conclusion is misleading. Men are better endowed (positive characteristics effect) but are penalized for working in the public sector (negative coefficients effect) at all points of the wage distribution. Compensating wage differentials may explain these results. Better endowed persons may be willing to work in the public sector despite being penalized for it in terms of pay as they value other aspects like job stability or employment protection.

If not attributed to compensating wage differentials, this penalization may present a disadvantage of the public compared to the private sector when it comes to recruiting men. The latter holds particularly in light of demographic change and increasing recruitment competition between the public and private sector. The resulting low attractiveness of the public sector for men may result in difficulties to find skilled male public employees and thus may represent a challenge for the public sector as it needs a qualified workforce to secure the provision of public services.

In order to better understand the role of compensating wage differentials for the PPWG, we drop in Section 7 civil servants from the analysis. As movers may also have different observable and unobservable characteristics (see Table A.1, Panel (b), Table A.2, Table A.3 and Table A.4 for descriptive statistics of sector and non-sector movers), we repeat in Appendix B the analysis separately for the sample of movers in public and private employment. The main insights do not change.

5 Incidental parameter bias correction

As is well known in the literature, panel-data studies with fixed time periods suffer from IPB. Bargain et al. (2018) used French data over the period 1988-2013 and a FE unconditional quantile approach to estimate the public-sector wage premium adjusted for IPB by using a recentered half-panel jackknife correction. Bargain et al. (2018) found only modest differences in the estimated premium with and without the correction at the very top of the wage distribution.

In contrast to Bargain et al. (2018), we present decomposition results of conditional quantile regressions and not of ceteris-paribus wage premiums. As described in Section 2, we estimate the counterfactual wages using simulations (Machado-Mata decompositions). Using the recentered half-panel jackknife for IPB-correction of the decomposition results would require to correct the wage equation for IPB before conducting simulations and not to correct the simulated outcome. This procedure would add a great amount of computational complexity. Nevertheless, we want to get a feeling of how the IPB affects our panel. Therefore, and for comparison with Bargain et al. (2018), we estimate the conditional public-sector wage premium for Germany along the distribution (see equation (8) below) and correct it for IPB using a recentered half-panel jackknife correction. The public-sector wage premium along the distribution is identified via movers.

Even though the long duration of our panel (1984-2017) tends to reduce the IPB, we apply a recentered half-panel jackknife correction for the following reasons.[7] Differencing out the FE (e.g., used for conditional linear models at the mean) does not work for quantile regression models. Consequently, every estimate is a function of the estimated FEs and cannot be estimated consistently when the number of periods is finite, i.e. if T is fixed and $N \to \infty$ (Bargain et al., 2018). In our case, we have more than 100,000 individual-year observations and 34 time periods. Note that also in cases with large numbers of individuals, the FE quantile estimators will be biased when the number of periods is finite (Bargain et al., 2018; Fernández-Val and Weidner, 2018).

As stated above, we apply a recentered half-panel jackknife correction for the IPB following Dhaene and Jochmans (2015) and Bargain et al. (2018). We thus correct the conditional public-sector wage premium for IPB as follows:

$$Q_\theta(y_i|z_i, x_i) = z_i\gamma_\theta + x_i\beta_\theta \tag{8}$$

$$y_i = z_i\gamma_\theta + x_i\beta_\theta + e_{\theta i} \tag{9}$$

where $Q_\theta(y_i|z_i, x_i)$ is the conditional quantile at θ of the dependent variable y (log hourly wages), given the covariates z (public-sector dummy) and x (individual characteristics). γ_θ gives the public-sector wage premium at θ and β_θ is a $k \times 1$ vector of coefficient estimates of individual characteristics at θ. Again, the distribution of the error term $e_{\theta i}$ is left unspecified and we assume that $Q_\theta(e_{\theta i}|z_i, x_i) = 0$. We translate equation (8) to the FEs framework as before, i.e. we have: $Q_\theta(\tilde{y}_{it}|z_{it}, x_{it}) = z_{it}\gamma_\theta + x_{it}\beta_\theta$, where $\tilde{y}_{it} = y_{it} - \hat{\alpha}_i$.

In order to correct for IPB we compute, apart from the estimate on the whole panel $\hat{\gamma}(\theta)$, also the estimates based on the first 17 periods ($T = 1$) $\hat{\gamma}_1(\theta)$, with $t \in 1984, 1985, \ldots, 2000$, and the last 17 ($T = 2$) periods $\hat{\gamma}_2(\theta)$, with $t \in 2001, 2002, \ldots, 2017$. The half-panel jackknife corrected estimator following Dhaene and Jochmans (2015) is then defined as:

$$\hat{\gamma}_{BC}(\theta) = \hat{\gamma}(\theta) - [0.5(\hat{\gamma}_1(\theta) + \hat{\gamma}_2(\theta)) - \hat{\gamma}(\theta)] = 2\hat{\gamma}(\theta) - 0.5(\hat{\gamma}_1(\theta) + \hat{\gamma}_2(\theta)) \tag{10}$$

where $\hat{\gamma}_{BC}(\theta)$ denotes the bias-corrected estimator at quantile θ, $\hat{\gamma}(\theta)$ denotes the estimate for the whole panel and $\hat{\gamma}_1(\theta)$ denotes the estimate for the first $T = 1$ panel and $\hat{\gamma}_2(\theta)$ for the second $T = 2$ panel.

[7] The potential IPB affects short panel estimations of nonlinear models with FE (Fernández-Val and Weidner, 2018) such as FE quantile regressions (Canay, 2011).

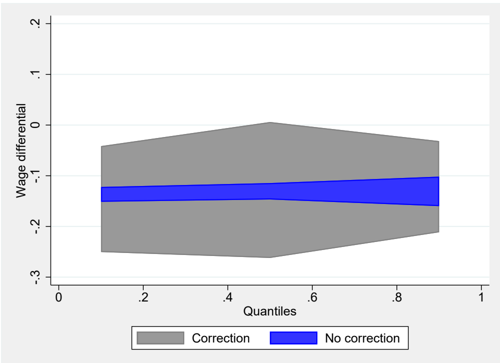
Observe that the distortion of the IPB is proportional to $\frac{1}{T}$ (see e.g., Bargain et al., 2018). The bias of $0.5(\hat{\gamma}_1(\theta) + \hat{\gamma}_2(\theta))$ is twice as large as the bias of $\hat{\gamma}(\theta)$. Consequently, the difference between these estimates provides an estimate of the IPB. However, reduction of the bias comes at the cost of increasing the variance of the estimator. We reduce the variance of the jackknife bias correction by incorporating the information about the coefficient estimate over all quantiles:

$$\hat{\gamma}_{RBC}(\theta) = \hat{\gamma}_{BC}(\theta) + \hat{\gamma} - \int_0^1 \hat{\gamma}_{BC}(\theta) d\theta \tag{11}$$

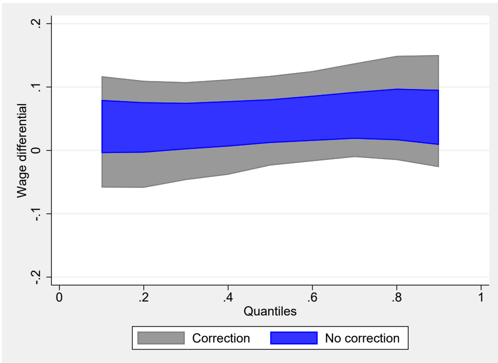
with $\hat{\gamma}_{RBC}(\theta)$ being the recentered corrected estimator as proposed by Bargain et al. (2018).

Figure 4 shows the public-sector wage premium along the distribution with and without correction. The point estimates are similar along the wage distribution. Further, the confidence bands of the estimates with and without correction do always overlap indicating that the two estimates are not statistically significantly different. These results hold for both men and women.

Figure 4: Conditional public-private wage premium along the wage distribution accounting for FEs with and without IPB correction



(a) Men



(b) Women

Notes: FE quantile regression with and without recentered half-panel jackknife correction. Shaded areas represent 95%-bootstrapped confidence bands (100 replications). Regressions run separately for men and women based on equation (8), with $Q_\theta(\tilde{y}_i|z_i, x_i)$, where $\tilde{y} = y - \hat{\alpha}$.

All in all, these findings suggest that IPB does not bias the point estimates.[8] In our

[8]Note that in the study of Bargain et al. (2018) this result holds as well, except at the very top, where their estimates (IPB-corrected and uncorrected) were statistically significantly different from each other. The authors, thus, concluded that the more compressed wage distribution in the French public sector was partly hidden by the IPB given a larger 90-10 public-sector wage penalty.

study (as well as in the study of Bargain et al., 2018), the number of time periods is relatively large and as the distortion of the IPB is proportional to $\frac{1}{T}$, IPB may not be a major concern for estimation of pay differences between the public and private sector in Germany.

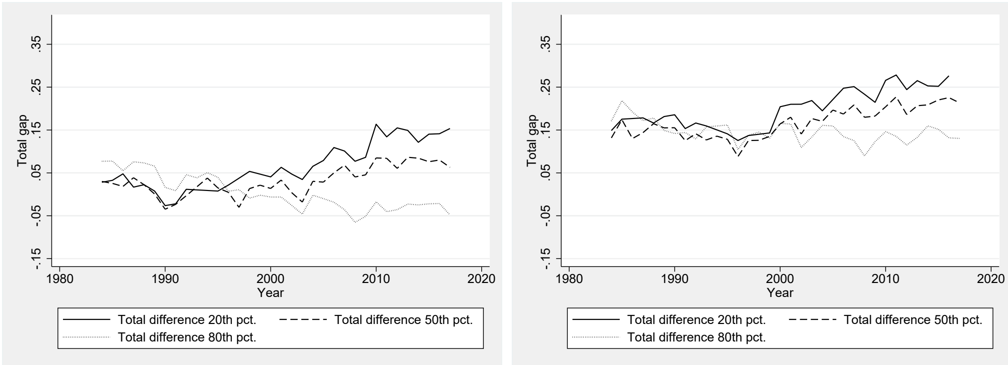
6 Evolution over time

In this Section, we look at the evolution of the PPWG over time. Differences in cyclical responses of wages between the public and private sector may lead to changes in the PPWG (Bargain et al., 2018; Giordano et al., 2011; Melly, 2005). Wages in the private sector generally vary pro-cyclically, while wages in the public sector may be more sticky. Moreover, institutional changes such as the erosion of collective bargaining or the German re-unification may have affected the PPWG.

Figure 5 shows the total estimated PPWG over time at selected percentiles, i.e. the gap based on the conditional wage model for men and women.[9] For men, we observe PPWGs roughly between -5% and 5% over time. The PPWG at the bottom, median and top evolves similarly until the mid 1990s. From then on, we observe a divergence of the gaps at different points of the distribution. While the median gap remains relatively stable over time, the bottom and top gap increase and decrease, respectively. For women, wages are higher in the public sector at all points in time. Over the last two decades, the PPWGs at different points of the distribution for women evolve relatively parallel over time. In line with the results for men, the gap at the median is most stable, while the bottom and top gap show an increasing and decreasing trend, respectively.

[9] For robustness, we show in Figure B.1 the annual total observed PPWGs that are not based on the conditional model. The main insights do not change.

Figure 5: Evolution of the total PPWG over time – Selected percentiles



(a) Men (b) Women

Notes: Figure represents the total gap estimated separately by year. The gap represents the differences in the observable distributions estimated using the conditional models. Variables controlled for in the regressions are the same as in the main analysis in Section 4.

All in all, the gaps for men and women started from similar levels in 1984, but diverged since the mid or late 1990s, respectively. Overall, the gap at the bottom increased, while the gap at the top decreased. We observe that the median gap has been most stable over time. These results hold for both men and women. The trend of the median PPWG may be explained by the German structure of wage negotiations (Melly, 2005). In Germany, collective bargaining agreements are negotiated by trade unions and employers (associations) at the sector and at the firm level (see e.g., Addison et al., 2017, for details). The negotiated agreements are valid for the entire workforce of a covered firm, regardless whether the corresponding employees are union members or not. Collective bargaining agreements cover most part of both sectors, but are predominant in the public sector (Giordano et al., 2011; Oberfichtner and Schnabel, 2019).[10]

Yet, the weakening of the German system of wage negotiation over the last two to three decades outside the public sector (Oberfichtner and Schnabel, 2019) may be one reason for the diverging trends of the PPWG since the late 1990s at the top and bottom of the wage distribution. Rising low-wage sectors (e.g., Grabka and Schröder, 2019) combined with the erosion of collective bargaining coverage implied a loss of the back-up that collective wage bargaining used to offer. As these phenomena occurred mainly in the private sector, wages for low-skilled employees or employees at the bottom of the distribution decreased in the private sector, while those in the public sector remained

[10]In 2015, 37% of all firms were subject to collective bargaining, while 96% of all public-sector firms were subject to collective bargaining (Oberfichtner and Schnabel, 2019).

relatively stable over time. Eventually this combination let to an increase of the PPWG at the bottom. The situation at the top or for high-skilled employees is different as with the erosion of collective wage bargaining, wages are increasingly contracted directly between employees and firms. In particular, high-skilled employees often end up with wages above collective agreement wage levels. Again, this bilateral contracting is predominant in the private sector and seldom in the public sector. As a result, private-sector wages increased at the top, while wages in the public sector were stable given a constant wage-setting mechanism in the public sector. As a consequence, the PPWG at the top decreased over time.

Finally, we do not observe a substantial impact of German re-unification in 1990 on the PPWGs at all points of the distribution. Similarly, privatization that took place in Germany until the mid 1990s (see e.g., Keller, 2010, for details) does not seem to have affected the gaps markedly. Moreover, different evolutions over time of the PPWGs at different percentiles demonstrate that it is important to use a FE quantile approach instead of relying on a cross-sectional approach.

7 Robustness check: Public sector without civil servants

In this Section, we exclude civil servants from the analysis for robustness. Civil servants are a particularly privileged subgroup predominant in the public sector.[11] They are protected against dismissal except in cases of pronounced misconduct. Additionally, pensions of civil servants are significantly higher compared to non-civil servants in the public sector and employees in the private sector (Riphahn, 2004; Schmidt and Müller, 2018). Including civil servants may therefore distort the decomposition results of the PPWG. Moreover, excluding civil servants helps to learn more about compensating wage differentials given special attributes (such as higher employment protection and better pensions) that apply only to this subgroup.

Table 2 shows descriptive statistics for the sample without civil servants. As in case of the main analysis (Table 1), the raw PPWG at the mean for men is small and statistically insignificant. The average PPWG for women amounting to 9% is smaller compared to the corresponding gap from the main analysis (16%) but remains high and statistically significant. The difference in years of schooling and tenure between the public and private sector are smaller for both men and women compared to the main analysis. This finding is not surprising as civil servants are on average older and better educated

[11] Note that, even tough,civil servants are predominantly employed in the public sector there may also be a small number civil servants in the private sector due to privatizations in the 1990s (Bieling, 2008).

than employees in the public sector (Federal Statistical Office, 2020). The difference in the existence of part-time employment and permanent contracts diminishes when civil servants are excluded. The latter is due to the fact that, by definition, civil servants have permanent contracts and are predominant in the public sector.

Table 2: Descriptive statistics sample excluding civil servants by sector and gender (movers and non-movers), selected controls

	(1)	(2)	(3)	(4)	(5)
Sector	Public		Private		
Variable	Mean	Std. dev.	Mean	Std. dev.	Difference
Panel (a): Men					
Log hourly wages	2.696	0.514	2.689	0.550	0.007
Schooling (in years)	12.515	2.629	12.157	2.583	0.358***
Age (in years)	44.826	9.721	42.199	9.987	2.627***
Experience (in years)	21.766	10.893	19.821	10.674	1.945***
Tenure (in years)	15.565	10.273	12.484	10.134	3.081***
Part-time (dummy)	0.035	0.185	0.011	0.102	0.024***
Permanent contract (dummy)	0.78	0.414	0.793	0.405	-0.013
Medium firm (dummy)	0.402	0.490	0.262	0.440	0.140***
Large firm (dummy)	0.294	0.455	0.241	0.427	0.053***
Married (dummy)	0.73	0.444	0.716	0.451	0.014
Observations	8,610		46,882		55,492
Panel (b): Women					
Variable	Mean	Std. dev.	Mean	Std. dev.	Difference
Log hourly wages	2.571	0.471	2.477	0.528	0.094***
Schooling (in years)	12.371	2.375	12.158	2.396	0.213***
Age (in years)	44.114	9.985	41.778	10.338	2.336***
Experience (in years)	12.564	9.731	12.074	9.295	0.490
Tenure (in years)	12.587	9.510	9.775	8.701	2.812***
Part-time (dummy)	0.398	0.489	0.348	0.476	0.05***
Permanent contract (dummy)	0.793	0.405	0.811	0.392	-0.018**
Medium firm (dummy)	0.381	0.486	0.223	0.416	0.158***
Large firm (dummy)	0.247	0.431	0.188	0.391	0.059***
Married (dummy)	0.615	0.487	0.566	0.496	0.049***
Observations	13,454		29,969		43,423

Notes: Sample excludes civil servants. Medium firm equals one if firm has between 200 and 1,999 employees. Large firm equals one if firm has at least 2,000 employees. Reported differences are based on a regression of a public-sector dummy on the selected variables. $*$, $**$ and $***$ denote significance at the 10%-, 5%- and 1%-level, respectively. Robust standard errors (clustered at the individual level) are used. Source: SOEP data v34.

Figure 6 shows the decomposition of the PPWG along the wage distribution for men and women when excluding civil servants using the standard pooled sample (Panel (a) and (b)) and the FE approach (Panel (c) and (d)). In case of the pooled sample approach, the PPWG for men is around zero at lower parts of the wage distribution and gets negative from the 60th percentile onwards (see Figure 6, Panel (a)). Thus, in line with the results from the main analysis (Figure 2), men at upper parts of the wage distribution in the public sector earn statistically significantly less compared to their colleagues in the private sector. In this sample, they do not have more generous pension rights or significantly higher employment protection than private-sector employees. Hence, a compensation for lower earnings in terms of higher pensions or employment protection is not relevant here. Thus, compensating wage differentials seem not to be crucial in explaining the male PPWG in the pooled sample.

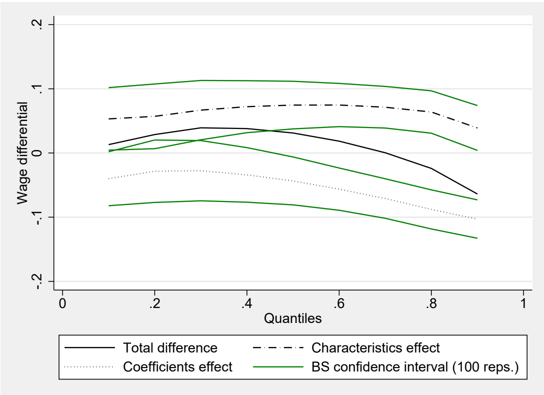
The PPWG for women based on the pooled sample excluding civil servants is also comparable to the PPWG in the main analysis. That is, the PPWG for women in the pooled sample is positive at all points of the wage distribution and converges to zero in the upper tail of the wage distribution when neglecting the panel structure of the data (see Figure 6, Panel (b)).

The PPWG accounting for FEs is shown in Figure 6, Panel (c) (for men) and Panel (d) (for women). For men, the PPWG is, as in the main analysis (Figure 3) around zero throughout the wage distribution due to a counterbalancing of the coefficients and the characteristics effect. As in case of the pooled sample approach, in the sample excluding civil servants the negative coefficients effect is unlikely to be due to compensating wage differentials. When taking the panel structure of the data into account, the PPWG for women is again positive at all points of the wage distribution (see Figure 6, Panel (d)). In the first half of the wage distribution this is due to a dominant positive characteristics effect, i.e. in the first part of the wage distribution women in the public sector are better endowed than their private-sector counterparts. This positive characteristics effect decreases along the wage distribution. At the same time, the initially (slightly) negative coefficients effect converges towards zero. Thus, in the upper part of the wage distribution the PPWG for women is smaller but still positive. However, the characteristics effect remains dominant throughout the distribution as it decreases relatively less compared to the results from the main analysis as one moves up the wage distribution.

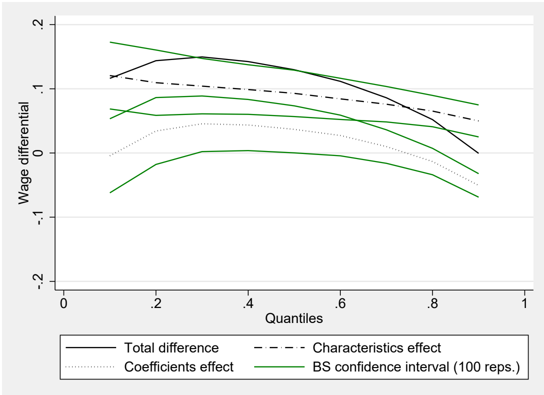
To sum up, the results when excluding civil servants from the analysis are comparable to our main results in Section 4. Only the influence of the characteristics and the coefficients effect on the PPWG for women applying FE changes slightly. Yet, the main conclusions persist.

This robustness test allows us to learn more about the role of compensating wage differentials for the PPWG at different points of the wage distribution. The results suggest that compensating wage differentials are not a main driver of the PPWG. That said, our findings suggest some sort of unequal treatment of men in the public sector.

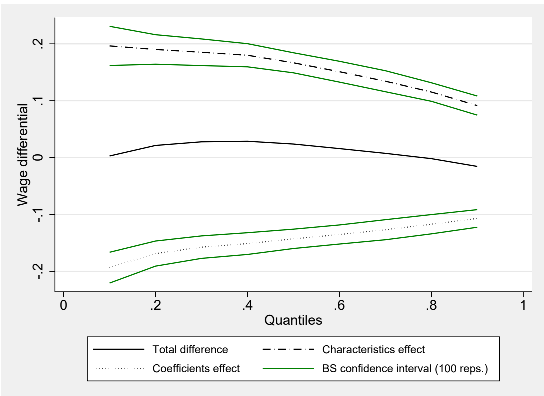
Figure 6: PPWG along the wage distribution – Excluding civil servants



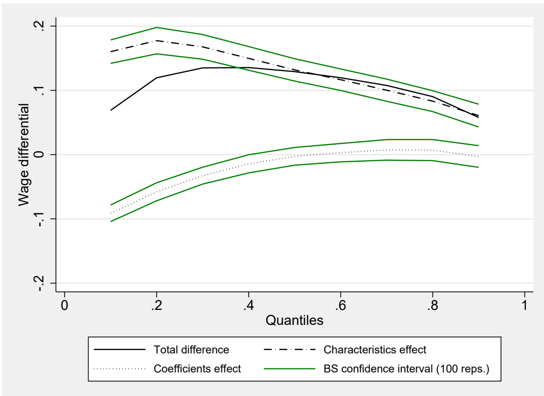
(a) Men – pooled sample approach



(b) Women – pooled sample approach



(c) Men – FE approach



(d) Women – FE approach

8 Conclusion

This paper estimates and decomposes the German PPWG along the distribution over the period 1984-2017. It is the first study for Germany that takes the panel structure of the data in the estimation of the PPWG into account. Using quantile regressions, we decompose the PPWG for both pooled cross sections and panel data. The former represents the standard estimation approach of PPWGs in the literature. For the latter, we use the approach suggested by Castagnetti and Giorgetti (2019). This approach allows us to decompose the PPWG into a characteristics effect (explained part) and a coefficients effect (unexplained part) accounting for FEs.

We find substantial differences in the decomposition of the German PPWG when accounting for the panel dimension of the data compared to the standard pooled sample approach. For both men and women, the characteristics and the coefficients effect, respectively, changes substantially when applying the FE quantile approach. As the FE quantile approach is more flexible and captures generally unobserved time-constant heterogeneity at the individual level, it may model the decomposition of the PPWG along the distribution more adequately. We also correct the public-sector wage premium along the distribution for IPB. The correction does not statistically significantly affect the results. This finding suggests that IPB is not a major problem in our study.

Looking at the results of our FE quantile approach in more detail, we see that women benefit from working in the public sector at all points of the wage distribution. Thus, the public sector is particularly attractive for women and therefore may be more successful in recruiting them. This advantage of the public sector is relevant when designing recruiting strategies and pay schemes in times of an increasing competition for (skilled) employees.

For men, we find only a small PPWG when applying the FE quantile approach. This finding may be interpreted as a balanced situation between the public and private sector when it comes to pay. However, the decomposition analysis shows that the total gap is misleading as the small PPWG is made up in almost equal terms of a positive characteristics and a negative coefficients effect. Although men in the public sector have better endowments at all points of the wage distribution (positive characteristics effect), they are at the same time penalized for working in the public sector at all points of the wage distribution (negative coefficients effect).

Our results suggest that this penalization is not due to compensating wage differentials for job stability or generous pension rights. In fact, we find persistent negative coefficient effects for men and bottom-income women when excluding civil servants, who enjoy special privileges like employment protection and generous pension rights. Combined with a zero total gap, the penalization may result in a low appeal of public-sector employment for men. Therefore, the public sector risks falling behind when competing with the private sector for high-skilled male employees. The latter does not apply to the same extent to women, as we observe positive PPWGs throughout the distribution.

Looking at the evolution of the PPWG over time suggests that the erosion of collective wage bargaining in Germany lead to diverging trends of the gap at different points of the distribution. Consequently, it is important to use quantile as well as panel-data approaches for the analysis of PPWGs. A caveat of our study is that we need to assume constant individual-level heterogeneity across the distribution. Nonetheless, our approach is more flexible compared to the methods present in the literature (e.g., Bargain et al., 2018).

Overall, our results suggest that the public sector should modify and adjust its pay schemes to merit-based ones – especially for men – in order to not be at risk of losing (skilled) employees. The latter is especially relevant in times of demographic change and an increasing competition for (skilled) employees.

References

Addison, J. T., C. Schnabel, and J. Wagner (2006): "The (parlous) state of German unions," *IZA Discussion Paper*, 2000.

Addison, J. T., P. Teixeira, A. Pahnke, and L. Bellmann (2017): "The demise of a model? The state of collective bargaining and worker representation in Germany," *Economic and Industrial Democracy*, 38, 193–234.

Bargain, O., A. Etienne, and B. Melly (2018): "Public Sector Wage Gaps over the Long-Run: Evidence from Panel Administrative Data," *IZA Discussion Paper*, 11924.

Bieling, H.-J. (2008): "Liberalisierung und Privatisierung in Deutschland: Versuch einer Zwischenbilanz," *WSI-Mitteilungen*, 61, 541–547.

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

Briel, S. and M. Töpfer (2020): "The gender pay gap revisited: Does machine learning offer new insights?" Tech. rep., FAU.

Canay, I. A. (2011): "A simple approach to quantile regression for panel data," *The Econometrics Journal*, 14, 368–386.

Castagnetti, C. and M. L. Giorgetti (2019): "Understanding the gender wage-gap differential between the public and private sectors in Italy: A quantile approach," *Economic Modelling*, 78, 240–261.

Chernozhukov, V., I. Fernández-Val, and B. Melly (2013): "Inference on counterfactual distributions," *Econometrica*, 81, 2205–2268.

Dhaene, G. and K. Jochmans (2015): "Split-panel jackknife estimation of fixed-effect models," *The Review of Economic Studies*, 82, 991–1030.

Dustmann, C. and M. E. Rochina-Barrachina (2007): "Selection correction in panel data models: An application to the estimation of females' wage equations," *The Econometrics Journal*, 10, 263–293.

Dustmann, C. and A. van Soest (1997): "Wage structures in the private and public sectors in West Germany," *Fiscal Studies*, 18, 225–247.

——— (1998): "Public and private sector wages of male workers in Germany," *European Economic Review*, 42, 1417–1441.

Ellguth, P. and S. Kohaut (2011): "Der Staat als Arbeitgeber: Wie unterscheiden sich die Arbeitsbedingungen zwischen öffentlichem Sektor und Privatwirtschaft?" *Industrielle Beziehungen*, 18, 11–38.

Federal Statistical Office (2015): *Germany's Population by 2060*, Wiesbaden: Federal Statistical Office.

——— (2020): *Fachreihe 14 Reihe 6: Personal des Öffentlichen Dienstes 2019*, Wiesbaden: Federal Statistical Office.

Fernández-Val, I. and M. Weidner (2018): "Fixed effects estimation of large-t panel data models," *Annual Review of Economics*, 10, 109–138.

Fortin, N., T. Lemieux, and S. Firpo (2011): "Decomposition methods in economics," in *Handbook of Labor Economics*, ed. by O. Ashenfelter and D. Card, Elsevier, vol. 4A, 1–102.

Giordano, R., D. Depalo, M. Coutinho Pereira, B. Eugène, E. Papapetrou, J. J. Pérez, L. Reiss, and M. Roter (2011): "The public sector pay gap in a selection of Euro area countries," *ECB Working Paper*, 1406.

GRABKA, M. M. AND C. SCHRÖDER (2019): "The low-wage sector in Germany is larger than previously assumed," *DIW Weekly Report*, 9, 117–124.

GRAMKE, K., A.-M. PLUME, M. HOCH, ET AL. (2012): "Arbeitslandschaft 2035," https://www.prognos.com/uploads/tx_atwpubdb/121218_Prognos_Studie_vbw_Arbeitslandschaft_2035.pdf, accessed: 2020-11-04.

GREGORY, R. G. AND J. BORLAND (1999): "Recent developments in public sector labor markets," in *Handbook of Labor Economics*, ed. by O. Ashenfelter and D. Card, Elsevier, vol. 3C, 3573–3630.

HOHENDANNER, C., E. OSTMEIER, AND P. RAMOS LOBATO (2015): "Befristete Beschäftigung im Öffentlichen Dienst," *IAB Forschungsbericht*, 12/2015.

HOSPIDO, L. AND E. MORAL-BENITO (2016): "The public sector wage premium in Spain: evidence from longitudinal administrative data," *Labour Economics*, 42, 101–122.

JUHN, C., K. M. MURPHY, AND B. PIERCE (1993): "Wage inequality and the rise in returns to skill," *Journal of Political Economy*, 101, 410–442.

JUNG, S. AND C. SCHNABEL (2011): "Paying more than necessary? The wage cushion in Germany," *Labour*, 25, 182–197.

JÜRGES, H. (2002): "The distribution of the German public-private wage gap," *Labour*, 16, 347–381.

KELLER, B. K. (2010): *Arbeitspolitik im öffentlichen Dienst*, Berlin: Edition Sigma.

KOENKER, R. AND G. BASSETT (1978): "Regression quantiles," *Econometrica*, 46, 33–50.

MACHADO, J. A. AND J. MATA (2005): "Counterfactual decomposition of changes in wage distributions using quantile regression," *Journal of Applied Econometrics*, 20, 445–465.

MELLY, B. (2005): "Public-private sector wage differentials in Germany: Evidence from quantile regression," *Empirical Economics*, 30, 505–520.

NEYMAN, J. AND SCOTT (1948): "Consistent estimates based on partially consistent observations," *Econometrica*, 16, l–32.

Oberfichtner, M. and C. Schnabel (2019): “The German model of industrial relations: (Where) Does it still exist?” *Jahrbücher für Nationalökonomie und Statistik*, 239, 5 – 37.

Pfeifer, C. (2011): “Risk aversion and sorting into public sector employment,” *German Economic Review*, 12, 85–99.

Prümer, S. (2020): “Ist der Staat der bessere Arbeitgeber? Arbeitsqualität im Öffentlichen und Privaten Sektor im Vergleich,” *Sozialer Fortschritt*, 69, 97–128.

Prümer, S. and C. Schnabel (2019): “Questioning the stereotype of the ”malingering bureaucrat”: Absence from work in the public and private sector in Germany,” *Kyklos*, 72, 570–603.

Riphahn, R. T. (2004): “Employment protection and effort among German employees,” *Economics Letters*, 85, 353–357.

Schmidt, W. and A. Müller (2018): “Germany: an intertwined two-part system of unilateralism and collective bargaining,” *Labor History*, 59, 71–86.

Appendix

A Further descriptive statistics

Table A.1 shows descriptive statistics for the full sample. We find a statistically significant PPWG of 7% (log approximation). Public-sector employees are on average statistically significantly better educated, older and stay longer with the same employer. In terms of labor market experience, employees in the two sectors do not statistically significantly differ from each other. Further, public-sector employees are more often part-time employees and have less often permanent contracts. This finding is in line with employment trends in the German public sector (Keller, 2010). Substantially more women as well as more married individuals are employed in the public sector. In fact, the public sector may be a particularly attractive employer for women due to more flexible working hours allowing thus for a better work-life balance.

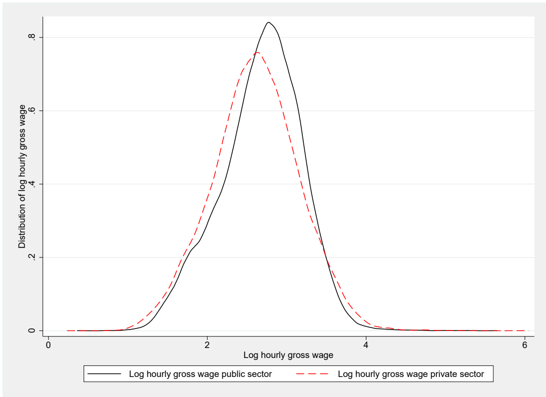
Table A.1: Descriptive statistics full sample (movers and non-movers) by sector, selected controls

	(1)	(2)	(3)	(4)	(5)
Sector	Public		Private		
Variable	Mean	Std. dev.	Mean	Std. dev.	Difference
Log hourly wages	2.673	0.51	2.606	0.551	0.067***
Schooling (in years)	13.193	2.89	12.176	2.519	1.017***
Age (in years)	44.504	10.014	42.019	10.139	2.485***
Experience (in years)	16.772	11.179	16.69	10.85	0.082
Tenure (in years)	15.425	10.804	11.401	9.725	4.024***
Part-time (dummy)	0.246	0.43	0.145	0.352	0.101***
Permanent contract (dummy)	0.745	0.436	0.798	0.401	-0.053***
Medium firm (dummy)	0.316	0.465	0.246	0.431	0.070***
Large firm (dummy)	0.328	0.469	0.221	0.415	0.107***
Married (dummy)	0.676	0.468	0.656	0.475	0.020***
Female (dummy)	0.528	0.499	0.396	0.489	0.116***
Observations	36,669		79,083		115,752

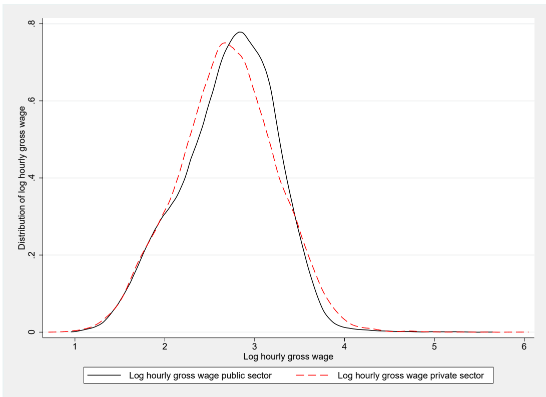
Notes: Figures refer to movers in both direction, i.e. into public and into private employment. Medium firm equals one if firm has between 200 and 1,999 employees. Large firm equals one if firm has at least 2,000 employees. Reported differences are based on a regression of a public-sector dummy on the selected variables. $*$, $**$ and $***$ denote significance at the 10%-, 5%- and 1%-level, respectively. Robust standard errors (clustered at the individual level) are used. Source: SOEP data v34.

Figure A.1, Panel (a), shows that wages between public- and private-sector employees are distributed differently, with generally higher wages for public-sector employees. However, at the upper part of the wage distribution, this relation reverses. The latter underlines that it is important to consider PPWGs along the distribution. The same holds for men (see Figure A.1, Panel (b)). For women, the wage distribution in the public sector is shifted to the right compared with the private sector implying that women earn more in the public than in the private sector at most points of the wage distribution. Looking only at the mean would not capture this variation along the distribution. Thus, it is important to go beyond the mean when looking at the PPWG.

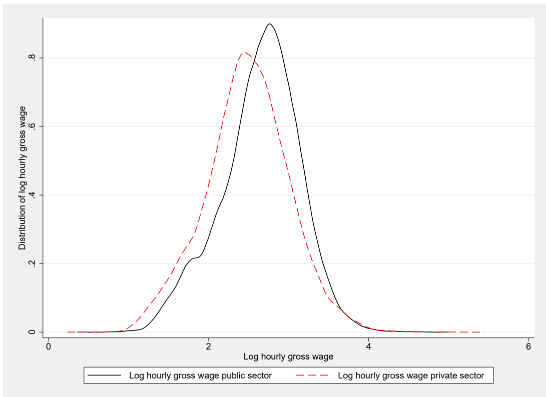
Figure A.1: Distribution of log hourly wages by sector



(a) Full Sample



(b) Men



(c) Women

Table A.2 presents descriptive statistics for movers across sectors in the full sample.[12] Compared with the full sample, the observed differences between the public and the private sector are less pronounced, except for working in a large firm in case of movers. The sign and the level of statistical significance of the observed differences between public- and private-sector employees persist. Thus, when sector switching takes place, observed differences decrease but remain statistically significantly different between employees in

[12]We do not distinguish between movers to the private sector and movers to the public sector in Table A.1.

the public and private sector.

Table A.2: Descriptive statistics movers by sector, selected controls

	(1)	(2)	(3)	(4)	(5)
Sector	Public		Private		
Variable	Mean	Std. dev.	Mean	Std. dev.	Difference
Log hourly wages	2.609	0.491	2.581	0.545	0.028***
Schooling (in years)	12.691	2.704	12.438	2.638	0.253***
Age (in years)	42.264	9.974	41.458	10.112	0.806***
Experience (in years)	14.274	10.217	14.397	10.144	-0.123
Tenure (in years)	10.751	9.629	9.829	9.258	0.922***
Part-time (dummy)	0.235	0.424	0.201	0.4	0.034***
Permanent contract (dummy)	0.75	0.433	0.783	0.412	-0.033***
Medium firm (dummy)	0.321	0.467	0.234	0.424	0.087***
Large firm (dummy)	0.278	0.448	0.218	0.413	0.060***
Married (dummy)	0.634	0.482	0.624	0.484	0.010***
Female (dummy)	0.580	0.494	0.508	0.499	0.072***
Observations	10,732		11,885		22,617

Notes: Medium firm equals one if firm has between 200 and 1,999 employees. Large firm equals one if firm has at least 2,000 employees. Reported differences are based on a regression of a public-sector dummy on the selected variables. $*$, $**$ and $***$ denote significance at the 10%-, 5%- and 1%-level, respectively. Robust standard errors (clustered at the individual level) are used. Source: SOEP data v34.

Table A.3 shows the number of movers across sectors. We define movers as individuals that change sectors at least once. In our sample, 20% of all individuals change the sector at least once over the period 1984-2017. Most individuals move to the public sector (18%). Sector switching – independently of the direction – is also more prevalent among women (see Table A.3).

Table A.4 shows descriptive statistics for movers and non-movers by gender. We see that male movers earn less than male non-movers (see Table A.4, Panel (a)). Also male movers outperform male non-movers in terms of schooling and are on average younger, have less labor market experience and tenure than non-movers. When it comes to part-time employment, type of contract and firm size, differences between male movers and non-movers are small and – partly – statistically insignificant. For women, we find no statistically significant wage gap between movers and non-movers (see Table A.4, Panel (b)). Similarly, we find no statistically significant difference in terms of schooling. Apart from that, our results for women are very similar to those for men in terms of age, labor market experience, tenure, part-time employment and firm size.

Generally, Table A.4 suggests that movers – both men and women – have on average better observable human capital and general labor market characteristics. Recall that

Table A.3: Sector movers

	(1) Full sample	(2) Men	(3) Women
Panel observations	115,752	65,064	50,688
Number of employees	12,800	6,887	5,913
Share of public-sector employees (in %)	31.68	26.58	38.22
Average periods observed by employee	6.7	7.02	6.29
Individuals with at least one sector move at all (in %)	2,182 (17.05)	925 (13.43)	1,257 (21.56)
Number of employees with at least one sector move at all (in %)	22,617 (19.54)	10,359 (15.92)	12,258 (24.18)
Number of employees moving from public to private sector (in %)	6,710 (8.45)	3,080 (6.44)	3,630 (11.5)
Number of employees moving from private to public sector (in %)	6,711 (18.47)	2,868 (16.66)	3,843 (20.1)

Notes: 'at least one sector move at all' may include both movers in the public and in the private sector. Source: SOEP data v34.

in times of demographic change, the public and private sector may compete particularly for these – better educated and skilled – employees.

Table A.4: Descriptive statistics for movers and non-movers by gender, selected controls

	(1)	(2)	(3)	(4)	(5)
	Mover		Non-mover		
Variable	Mean	Std. dev.	Mean	Std. dev.	Difference
Panel (a): Men					
Log hourly wages	2.666	0.539	2.699	0.544	-0.033**
Schooling (in years)	12.647	2.812	12.399	2.704	0.248**
Age (in years)	41.726	9.843	43.183	10.089	-1.457***
Experience (in years)	18.34	10.331	20.669	10.741	-2.329***
Tenure (in years)	11.753	10.382	14.285	10.69	-2.532***
Part-time (dummy)	0.029	0.167	0.021	0.144	0.008*
Permanent contract (dummy)	0.757	0.429	0.773	0.419	-0.016*
Medium firm (dummy)	0.269	0.443	0.274	0.446	-0.005
Large firm (dummy)	0.28	0.449	0.276	0.447	0.004
Married (dummy)	0.699	0.459	0.726	0.446	-0.027*
Observations	10,359		54,705		65,064
Panel (b): Women					
Log hourly wages	2.534	0.496	2.545	0.529	-0.011
Schooling (in years)	12.484	2.546	12.605	2.659	-0.121
Age (in years)	41.938	10.23	42.839	10.301	-0.901***
Experience (in years)	10.957	8.718	12.487	9.637	-1.53***
Tenure (in years)	9.01	8.374	11.803	9.671	-2.793***
Part-time (dummy)	0.376	0.484	0.376	0.484	0
Permanent contract (dummy)	0.776	0.417	0.802	0.399	-0.026***
Medium firm (dummy)	0.281	0.449	0.256	0.436	0.025**
Large firm (dummy)	0.217	0.412	0.231	0.421	-0.014
Married (dummy)	0.569	0.495	0.591	0.492	-0.022
Observations	12,258		38,430		50,688

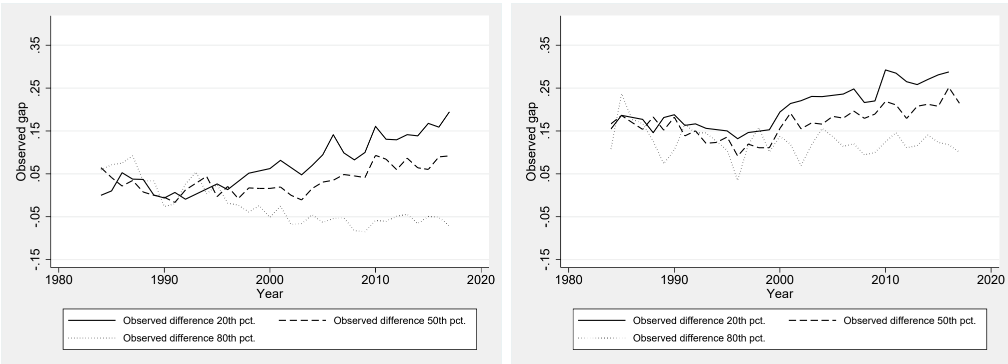
Notes: Reported figures refer to individuals that move at least once. Medium firm equals one if firm has between 200 and 1,999 employees. Large firm equals one if firm has at least 2,000 employees. Reported differences are based on a regression of a mover dummy on the selected variables. $*$, $**$ and $***$ denote significance at the 10%-, 5%- and 1%-level, respectively. Robust standard errors (clustered at the individual level) are used. Source: SOEP data v34.

B Further robustness tests

In this Section, we show the observed PPWG over time (Section B.1) and repeat the estimation analysis for both movers in the public (Section B.2) and the private sector (Section B.3). In case of the mover analysis, we show descriptive statistics and decomposition results.

B.1 Observed PPWG over time

Figure B.1: Evolution of the observed PPWG over time – Selected percentiles



(a) Men (b) Women

Notes: Figure represents the observed gap separately by year. The represented gap does not rely on the conditional models.

B.2 Robustness check: Public-sector movers only

For robustness, we now restrict our sample to movers in the public sector and non-movers. Table B.1 shows that by excluding private-sector movers, we have relatively more public-sector employees (26% of all men and 38% of all women are public-sector employees). Further, the PPWG is slightly higher for men and women compared to the main analysis (Table 1), where we consider both movers in the public and the private sector. This finding suggests that better endowed individuals change into public work and that this move pays off for them. In fact, the difference in educational attainment and experience between public- and private-sector employees is more pronounced in this sample, both for men and women, while tenure is slightly shorter (see Table B.1). There are no changes in differences in part-time employment and in having a permanent contract between the public and private sector when only considering movers in the public sector and non-movers.

Table B.1: Descriptive statistics public-sector movers and non-movers by sector and gender, selected controls

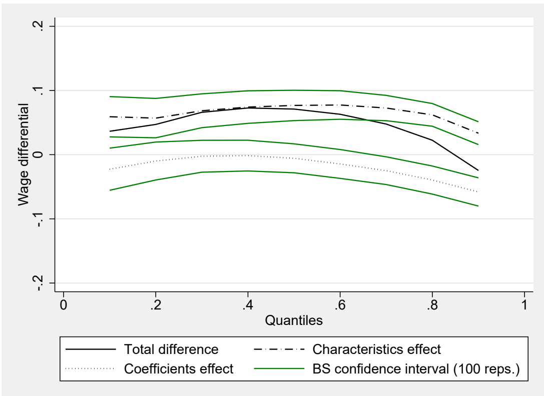
	(1)	(2)	(3)	(4)	(5)
Sector	Public		Private		
Variable	Mean	Std. dev.	Mean	Std. dev.	Difference
Panel (a): Men					
Log hourly wages	2.712	0.524	2.689	0.550	0.023*
Schooling (in years)	13.206	2.937	12.158	2.583	1.048***
Age (in years)	45.34	9.826	42.211	9.987	3.129***
Experience (in years)	22.017	10.525	19.836	10.675	2.181***
Tenure (in years)	18.204	10.943	12.522	10.164	5.682***
Part-time (dummy)	0.054	0.226	0.011	0.102	0.043***
Permanent contract (dummy)	0.712	0.453	0.793	0.405	-0.081**
Medium firm (dummy)	0.311	0.463	0.261	0.439	0.05***
Large firm (dummy)	0.375	0.484	0.242	0.428	0.133***
Married (dummy)	0.745	0.436	0.716	0.451	0.029**
Observations	16,407		47,017		63,424
Panel (b): Women					
Log hourly wages	2.65	0.493	2.478	0.528	0.172***
Schooling (in years)	13.255	2.861	12.156	2.393	1.099***
Age (in years)	44.226	9.955	41.776	10.330	2.45***
Experience (in years)	12.575	9.745	12.08	9.290	0.495*
Tenure (in years)	13.814	10.120	9.815	8.720	3.999***
Part-time (dummy)	0.417	0.493	0.348	0.476	0.069***
Permanent contract (dummy)	0.782	0.413	0.81	0.392	-0.028***
Medium firm (dummy)	0.326	0.469	0.223	0.416	0.103***
Large firm (dummy)	0.291	0.454	0.19	0.393	0.101***
Married (dummy)	0.624	0.484	0.566	0.496	0.058***
Observations	18,170		30,073		48,243

Notes: Sample restricted to movers in the public sector Medium firm equals one if firm has between 200 and 1,999 employees. Large firm equals one if firm has at least 2,000 employees. Reported differences are based on a regression of a public-sector dummy on the selected variables. $*$, $**$ and $***$ denote significance at the 10%-, 5%- and 1%-level, respectively. Robust standard errors (clustered at the individual level) are used. Source: SOEP data v34.

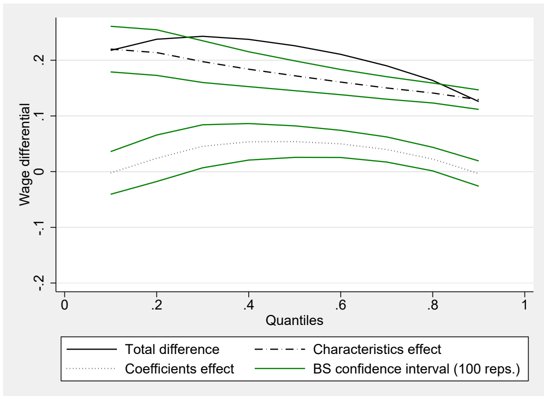
Figure B.2 shows that the main conclusions on the PPWG persist when restricting the sample to public-sector movers and non-movers. For men, we still see a slightly positive PPWG in the pooled sample, which turns negative after the 80th percentile (see Figure B.2, Panel (a)). Using the FE approach, the observed PPWG is close to zero at all points of the wage distribution due to a counterbalancing of the coefficients and characteristics effect (Figure B.2, Panel (c)).

Looking at the PPWG for women in the pooled sample, we see that conditional wages of women working in the public sector are higher than in the private sector independently of their rank in the wage distribution (Figure B.2, Panel (b)). When we apply the FE approach, the PPWG for women is positive at all points of the wage distribution driven by both a positive coefficients and a positive characteristics effect. All in all, the results from the main analysis in Section 4 are robust to excluding private-sector movers.

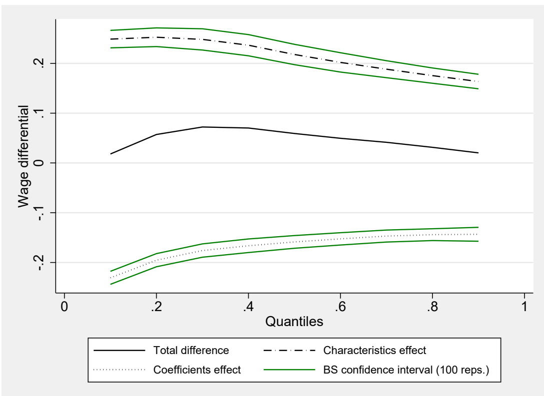
Figure B.2: PPWG along the wage distribution – public-sector movers and non-movers



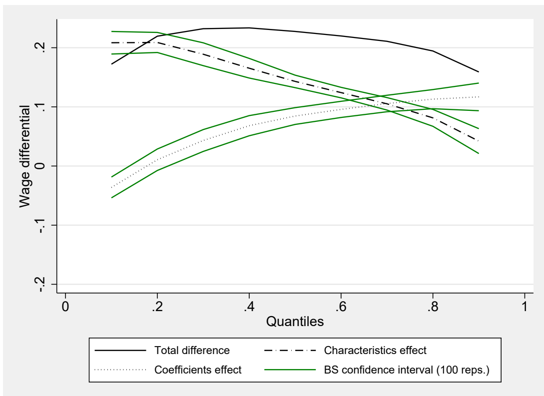
(a) Men – pooled sample approach



(b) Women – pooled sample approach



(c) Men – FE approach



(d) Women – FE approach

B.3 Robustness check: Private-sector movers only

Finally, we restrict our sample to movers in the private sector and non-movers. We do so, in order to account for the fact that movers to the private sector may be a specific subsample. Table B.2 shows the descriptive statistics for this sample. The PPWG for men is statistically insignificant, while we find a positive and statistically significant PPWG for women. These findings are similar to those of Table 1 from the main analysis. For men, differences in observable characteristics persist in sign and size compared to the main analysis. For women, differences in age between the public and the private sector are smaller, while difference in tenure are higher when only considering private-sector movers and non-movers compared to the descriptive statistics of the main analysis. Despite these changes in size, public- and private-sector employees are still statistically significantly different from each other in terms of general observable characteristics.

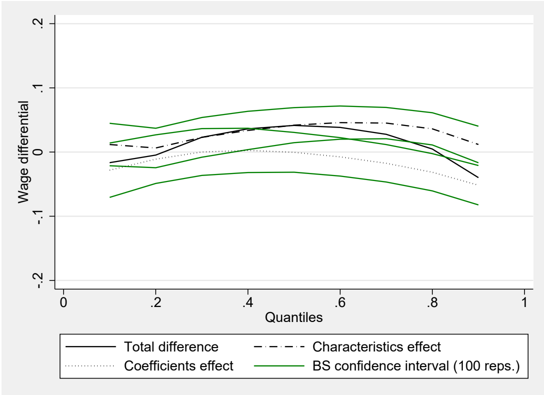
Figure B.3 shows the PPWG along the wage distribution for men and women for both the pooled sample and the FE approach when restricting the sample to private-sector movers and non-movers. Applying the pooled sample approach, we find that the PPWG for men is only slightly positive and turns negative after the 80th percentile (see Figure B.3, Panel (a)). When taking the panel structure into account and using the FE approach, the PPWG for men is around zero at all points of the wage distribution (see Figure B.3, Panel (c)). Thus, the findings for men when only dropping public-sector movers are in line with those of the main analysis.

Table B.2: Descriptive statistics sample private-sector movers and non-movers by sector and gender, selected controls

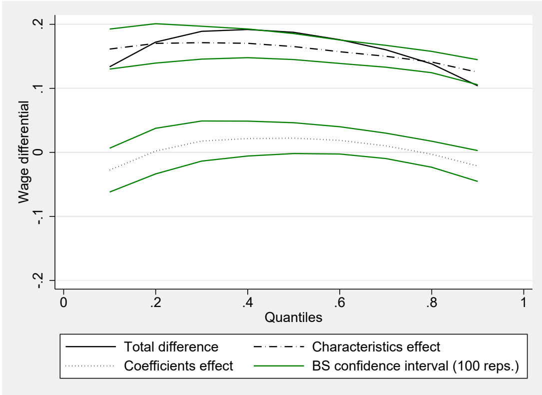
	(1)	(2)	(3)	(4)	(5)
Sector	Public		Private		
Variable	Mean	Std. dev.	Mean	Std. dev.	Difference
Panel (a): Men					
Log hourly wages	2.703	0.53	2.695	0.549	0.008
Schooling (in years)	13.225	2.945	12.178	2.594	1.047***
Age (in years)	45.142	10.001	42.31	9.989	2.832***
Experience (in years)	21.835	10.679	19.903	10.689	1.932***
Tenure (in years)	18.371	10.913	12.55	10.19	5.821***
Part-time (dummy)	0.054	0.225	0.011	0.103	0.043***
Permanent contract (dummy)	0.702	0.457	0.795	0.404	-0.093***
Medium firm (dummy)	0.302	0.459	0.261	0.439	0.041***
Large firm (dummy)	0.381	0.486	0.243	0.429	0.138***
Married (dummy)	0.739	0.439	0.716	0.451	0.023*
Observations	15,820		46,376		62,196
Panel (b): Women					
Log hourly wages	2.642	0.503	2.489	0.525	0.153***
Schooling (in years)	13.306	2.867	12.178	2.404	1.128***
Age (in years)	43.947	10.118	41.908	10.332	2.039***
Experience (in years)	12.377	9.757	12.118	9.33	0.259
Tenure (in years)	13.946	10.219	9.895	8.773	4.051***
Part-time (dummy)	0.426	0.494	0.35	0.477	0.076***
Permanent contract (dummy)	0.773	0.419	0.813	0.39 0	-0.040***
Medium firm (dummy)	0.32	0.466	0.222	0.416	0.098***
Large firm (dummy)	0.29	0.454	0.191	0.393	0.099***
Married (dummy)	0.623	0.485	0.568	0.495	0.055***
Observations	17,175		29,670		46,845

Notes: Sample restricted to movers in the private sector. Medium firm equals one if firm has between 200 and 1,999 employees. Large firm equals one if firm has at least 2,000 employees. Reported differences are based on a regression of a public-sector dummy on the selected variables. $*$, $**$ and $***$ denote significance at the 10%-, 5%- and 1%-level, respectively. Robust standard errors (clustered at the individual level) are used. Source: SOEP data v34.

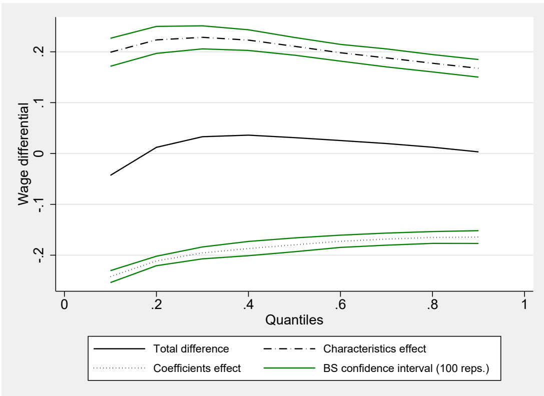
Figure B.3: PPWG along the wage distribution – private-sector movers and non-movers



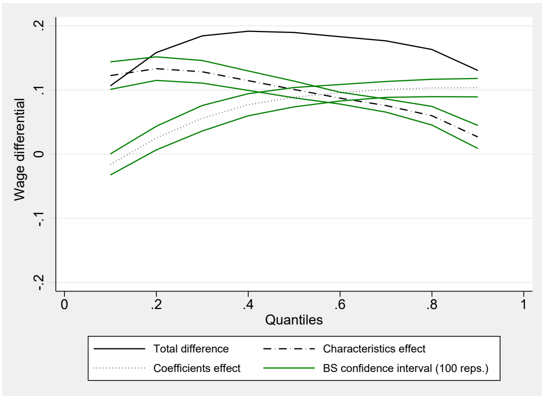
(a) Men – Pooled sample approach



(b) Women – Pooled sample approach



(c) Men – FE approach



(d) Women – FE approach

For women, the PPWG in Figure B.3, Panel (b), is positive at all points of the wage distribution. The gap is – as in the main analysis – driven by a positive characteristics effect. Applying the FE approach, the female PPWG remains positive at all points of the wage distribution (see Figure B.3, Panel (d)). The size of the PPWG for women is thereby similar compared to the results from the main analysis (Figure 3). Moreover, the influence of the coefficients and the characteristics effect on the PPWG for women does not change when restricting the sample to private-sector movers (Figure B.3, Panel (d)).

Hence, excluding public-sector movers from the sample does neither for men nor for women change our conclusions from the main analysis.

In der Diskussionspapierreihe sind kürzlich erschienen:

Recently published Discussion Papers:

116	Bonaccolto-Töpfer, M., Castagnetti, C., Prümer, S.	Does it Pay to Go Public? Understanding the Public-Private Sector Wage Gap in Germany	03/2021
115	Kovalenko, T., Töpfer, M.	Cyclical dynamics and the gender pay gap: A structural VAR approach	03/2021
114	Oberfichtner, M., Schnabel, C., Töpfer, M.	Do unions and works councils really dampen the gender pay gap? Discordant evidence from Germany	08/2020
113	Schnabel, C.	Union Membership and Collective Bargaining: Trends and Determinants	07/2020
112	Fackler, D., Hölscher, L., Schnabel, C., Weyh, A.	Does working at a start-up pay off?	01/2020
111	Briel, S., Töpfer, M.	The Gender Pay Gap Revisited: Does Machine Learning offer New Insights?	11/2019
110	Kölling, A., Schnabel, C.	Owners, external managers, and industrial relations in German establishments	11/2019
109	Hinz, T., Lechmann, D.	The role of job satisfaction and local labor market conditions for the dissolution of worker-job matches	07/2019
108	Prümer, S., Schnabel, C.	Questioning the stereotype of the “malingering bureaucrat”: Absence from work in the public and private sector in Germany	05/2019
107	Prümer, S.	Ist der Staat der bessere Arbeitgeber? Arbeitsqualität im Öffentlichen und Privaten Sektor in Deutschland	05/2019
106	Bossler, M., Oberfichtner, M., Schnabel, C.	Employment adjustments following rises and reductions in minimum wages: New insights from a survey experiment	08/2018

Eine aktualisierte Liste der Diskussionspapiere findet sich auf der Homepage:
http://www.arbeitsmarkt.rw.fau.de/

An updated list of discussion papers can be found at the homepage:
http://www.arbeitsmarkt.rw.fau.de