Received: 16 April 2021 | Revised: 11 March 2022 | Accepted: 13 April 2022
DOI: 10.1002/jae.2926

RESEARCH ARTICLE

WILEY Journal of APPLIED ECONOMETRICS

Did earnings mobility change after minimum wage introduction? Evidence from parametric and semi-nonparametric methods in Germany

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Summary

We analyze the evolution of earnings mobility in Germany between 2011 and 2018. We use transition matrices and parametric and semi-nonparametric copula models to assess the impact of the introduction of the national minimum wage on January 1, 2015, on individual positional persistence in the wage distribution. We find a drop in mobility at the bottom of the distribution. This is confirmed both by the parametric and the semi-nonparametric methods used. Prediction accuracy of the semi-nonparametric model is higher than that of the fully parametric model.

KEYWORDS

earnings dynamics, functional copula model, minimum wage, positional persistence, semi-nonparametric estimation

1 | INTRODUCTION

The aim of this paper is to assess the impact of the introduction of a statutory minimum wage on January 1, 2015, on earnings mobility patterns in Germany.[1] The contribution of this paper is twofold. First, we compare and contrast the performance of econometric methods characterized by different degrees of flexibility. Second, we show that the two-step semi-nonparametric copula model proposed by Naguib and Gagliardini (2020) excels at depicting mobility patterns; that is, it allows for more flexibility and has a better fit to the data.

The present paper is an extension of Bonhomme and Robin (2009). The major difference between that paper and ours is that Bonhomme and Robin (2009) consider a parametric copula family, namely, the Plackett copula (Plackett, 1965), while our copula specification is semi-nonparametric. This choice is dictated by our interest in discovering nonparametrically the patterns of dependence between the current and past earnings ranks. The price to pay for this increase in flexibility describing earnings mobility patterns is that the inclusion of transitions into and out of unemployment into our model is computationally intractable.[2] On the other hand, the advantage is that our model allows to estimate the degree of

[Correction added on 10-Oct-2022, after initial online publication. A duplicate of this article was published under the doi:10.1002/jae.2925. This duplicate has now been deleted and its DOI redirected to this version of the article.]

[1]This minimum wage has been fixed at 8.5 euros/h starting on January 1, 2015, and it has been raised to 8.84 euros/h since January 1, 2017. It was further raised to 9.19 euros/h in 2019 and to 9.35 euro/h in 2020. By law, it is revised at least every 2 years.

[2]The estimation of the semi-nonparametric copula model implies the computation of several integrals by Monte Carlo simulation. Given the size of the dataset used in the present paper, this implies that a single estimation, which is performed with the software R, requires more than 16 h working

earnings mobility virtually for any individual (i.e., conditional on the value of his/her covariates) at any point of the rank distribution. This is an improvement over the fully parametric model. Even if we are not able to explicitly include transitions into and out of unemployment in our model, in the exploratory data analysis, we study raw earnings transitions matrices, with and without including a separate state for zero earnings observations. This provides us with some intuition on the employment effects of the minimum wage reform.

Estimation is composed by three separate steps. In the first step, we obtain earnings residuals from a latent class panel regression in the spirit of Bonhomme and Robin (2009), and we compute the corresponding empirical residual ranks as percentiles of the empirical cross-sectional distribution of the residuals. Then, we estimate a semi-parametric single-index model for the conditional distribution of the rank at a given date conditionally on the individual characteristics. Finally, we estimate the semi-nonparametric copula model with the method of Sieves. As opposed to most of the existing literature on individual earnings dynamics, we model the dynamics of the ranks of the residuals, instead of modelling the dynamics of the residuals directly. This last option would correspond to the study of absolute earnings mobility (e.g., Hu et al. (2019)), whereas we focus on so-called relative or rank mobility. Finally, after performing the three above-described steps, we use the estimation results to recover the predicted wage for each individual at each time t. Hence, we compute estimated transition matrices between past wage (recorded in the data) and current predicted wage. In the third estimation step, we use both a fully parametric copula (in the spirit of, e.g. Bonhomme and Robin (2009)) and a semi-nonparametric copula[3] to estimate earnings mobility patterns. In the empirical application, we contrast the estimates from the two models, and we provide empirical evidence that our semi-nonparametric approach improves the understanding of earnings mobility patterns. As mentioned above, we aim at assessing whether the policy change of 2015 brought about a change in the degree of earnings mobility. We find evidence of a drop in mobility at the bottom of the earnings distribution. This finding is confirmed both by our preliminary data analysis and by the estimation results of the parametric and the seminonparametric models. Further, when comparing the prediction accuracy of the parametric and of the semi-nonparametric models, we find that the latter has a better performance than the former.

The minimum wage literature is wide, and a comprehensive review of it lies beyond the scope of the present paper. However, to the best of our knowledge, the influence of a minimum wage on the degree of earnings mobility, that is, the defining feature of the present paper, has not been put under scrutiny yet. When analyzing the impact of the introduction of a statutory minimum wage, a fundamental distinction has to be made between immediate reactions to the minimum wage and permanent changes in the wage structure and in wage dynamics.[4] Immediate changes taking place between 2014 and 2015 may include wage cuts for those workers being slightly above the minimum wage threshold (as firms need to keep their labor costs approximately constant) or overall wage raises, in order to preserve wage differentials and their relationship with employees' productivity differentials. This last phenomenon is called “within-establishment positive spillover” (Bossler & Gerner, 2020). The two types of immediate reactions described above are not captured by the our empirical analysis performed in Section 4. On the contrary, the focus of the present paper lies in permanent changes in earnings dynamics due to the minimum wage introduction. The main theoretical channels that may cause permanent changes in the wage structure and in wage dynamics following the introduction of a minimum wage are described in the following.

The first transmission channel is linked to firms substituting low-skilled workers with high skilled ones after the introduction of a minimum wage. Indeed, after a minimum wage has been introduced, the price of low-skilled workers relative to that of high-skilled workers becomes higher, thus encouraging the firms to substitute low-skilled with high-skilled workers (Clemens (2021); Giuliano, 2013; Neumark et al. (2004); Neumark and Wascher (2008); Zavodny (2000)). This may lead to a rise in the demand for certain types of more skilled labor, depending on substitutability, and hence to increased wages for certain types of workers already above the minimum. Further, it may lead firms to reorganize how they use their workforce to realign the marginal products of their minimum wage workers with the new minimum, and this may have effects on the marginal products of other workers (Stewart, 2012). Thus, minimum wages may cause per-

on a server with 16 cores. Adding a part on transitions into and out of unemployment to the semi-nonparametric copula model would further notably lengthen the required estimation time. Using more efficient estimation packages in R (e.g., nlm, optimx, or DEoptim) only marginally reduces the required computational time.

[3]This model is extensively described in Naguib and Gagliardini (2020).

[4]In the present paper, we use the terms “wage” and “earnings” interchangeably. By both terms, we mean the sum of all wages and salaries earned by the individual during a certain period (i.e., a year in our data). Further, most of the analyses presented are based on hourly wages/hourly earnings, that is, the total annual sum of all wages and salaries earned by the individual, divided by the total number of hours that the individual has worked in that given year.

manent changes in the mix of low-skilled/high-skilled workers employed by the firms. This may lead to (i) an increase in downward mobility of low-educated workers from the first bottom decile to the zero earnings decile, if low-skilled workers are laid off,[5] (ii) a decrease in upward mobility in the bottom part of the distribution for low-educated workers, as promotions and pay raises become rarer for them, and (iii) an increase in upward earnings mobility in the bottom part of the distribution for high-educated workers (for the opposite reasons: promotions and pay raises become more frequent for them).

Consistently with the hypothesis of input substitution by the firm, in our empirical results (see Figure 4 in Section 4), we we find evidence of a drop in mobility for workers with a high school diploma being at the bottom of the distribution. On the other hand, we witness an increase in mobility for workers with a university degree initially being at the same point (i.e., in the bottom decile of the distribution). At the aggregate level (i.e., transition matrices), the former effect prevails; that is, we notice a drop in positional mobility at the bottom of the distribution after the reform, since in our data, most workers in the bottom decile have a high school diploma (around 67%). However, we do not record any relevant change in downward mobility from the first bottom earnings decile to the zero earnings state. This can be due to (i) the absence of meaningful disemployment effects, as suggested in the literature, or (ii) to the fact that such transitions are non-permanent and already materialized between 2014 and 2015. In the latter case, the short run-effect would not be captured by the empirical design of the present paper. Further, consistently with Neumark et al. (2004), we also find that higher wage workers are essentially not affected by the reform (i.e., our estimated transition probabilities in the middle and upper part of the distribution do not relevantly change after 2015).

Consequently to the change in the low-skilled/high-skilled workers mix employed by firms, minimum wages have also been found to promote innovation and to push firms to adopt more technologically intensive production techniques (Askenazy, 2003; Clemens, 2021). Minimum wages tend to raise overall productivity by eliminating low-productivity jobs (Dustmann et al., 2022; Nickell & Layard, 1997). Permanent changes induced by the introduction of (or the increase in) a minimum wage also include greater incentives for the workers to accumulate human capital and for the firms to pay for training (Acemoglu & Pischke, 1999; Cahuc & Michel, 1996; Neumark & Wascher, 2008; Romer, 1986, 1989). However, we are not able to test this hypothesis, as in our data, we only observe education that takes place before labor market entry. We do not observe on-the-job-training.

The second transmission channel from minimum wage to wage mobility (which is the inverse of wage persistence) is explained by the job ladder model. In a job ladder model, minimum wages reduce job-to-job transitions by lowering the arrival rate of better-paying job offers. This means that minimum wages reduce incentives to on-the-job search (Dube et al., 2016). Indeed, in this model, the arrival of a superior offer affects a worker's willingness to stay at his or her current job; therefore, changes in the offer wage distribution can affect the steady-state rate at which workers leave their jobs to take better ones (Dube et al., 2016). If (as assessed by the previous literature) a minimum wage induces compression of the wage distribution, this then entails a lower rate of job-to-job transitions. This may translate into a lower degree of (upward) wage mobility overall across the wage distribution. Empirically, we do not find confirmation of this transmission channel in the data.

The third transmission channel is explained by search and match models. From the viewpoint of these models, a higher (or new) minimum wage increases the gap between the expected returns to employment relative to unemployment, inducing additional search effort from unemployed workers (even if it also reduces demand for labor expressed by the firms, by raising the marginal cost of employing a new worker). By increasing the pool of searching workers (and the intensity of their searching), the minimum wage improves the quality of matches between employers and employees, thus generating surplus (Meer & West, 2016). This may lead to an increase in upward mobility out of the zero earnings state (i.e., more individuals exit from unemployment). Further, surplus creation due to higher productivity may also lead to higher upward earnings mobility in general across the earnings distribution. Empirically, we record slight increases in the shares of those who leave the zero earnings state to reach the middle and upper deciles (i.e., from the fifth upwards) after 2015, which is consistent with the predictions of the search and match model.

Finally, there could be another reason why earnings mobility is influenced by the introduction of a minimum wage. Given that a minimum wage is expected to decrease the variance of wages, at least in the bottom deciles, this wage compression may make it easier to jump from one decile to another ("mechanically"), just because there would be less wage dispersion in the bottom deciles. A test for the difference in variances on our data shows that we can reject the hypothesis

[5]This is more an "immediate" adjustment than a permanent change. However, depending on the institutional framework and on the degree of input substitutability by the firms, it may take a considerable time span (i.e., more than one year) in order to be completed. Hence, we may find traces of it in our estimations.

that variance of hourly wages was the same before and after minimum wage introduction within the first bottom hourly wage decile (the corresponding p value is zero). The alternative hypothesis of this test is that the variance diminished after 2015. We obtain the identical test result within, respectively, the second and the third bottom hourly wage deciles. Between-deciles variance in hourly wage in the bottom part of the hourly wage distribution also decreased after 2015. This drop in variance is statistically significant at the 99% confidence level.[6] This means that we actually record a drop in earnings variance in our data after 2015. However, in Sections 3 and 4, we record empirically a decrease in upward mobility out of the first bottom decile and, in particular, a (slight) decline in the probability of jumping from the first bottom to the second-bottom hourly earnings decile (22% after 2015 vs. 24% before). Further, the share of individuals passing from the second bottom decile to the first bottom decile after 1 year also dropped (from around 21% to around 18%), meaning that we also witness a decrease in downward wage mobility towards the bottom earnings decile. Hence, the other transmission channels must have had a greater role in determining permanent changes in mobility patterns after 2015.

The remainder of the paper is structured as follows. Section 2 presents the semi-nonparametric econometric model. Section 3 is devoted to the description of the dataset and to some exploratory analysis. In Section 4, estimation results of the parametric and semi-nonparametric models are presented and discussed. Section 5 concludes. Appendix A in the supporting information presents the details of the estimation strategy for the semi-nonparametric copula model. Appendix B in the supporting information presents additional data analysis and robustness checks.

2 | THE MODEL

The aim of this section is to distil the key features of the analytic framework developed in Naguib and Gagliardini (2020). In particular, this section relies on sections 2 and 3 in Naguib and Gagliardini (2020). For the theoretical details, as well as for the proofs of theorems and propositions, we refer the interested reader to the above-mentioned companion paper. The objects of both the parametric and the semi-nonparametric models are the individual residual earnings ranks, that is, the individual positions in the cross-sectional distribution of the earnings residuals at a given date. In order to obtain the earnings residuals, we first regress log earnings on age and age squared, in order to disentangle the “deterministic” earnings component from the residual component. The model reads

$$Earnings_{i,t} = \alpha_1 Age_{it} + \alpha_2 Age_{it}^2 + \sigma_t \eta_i + \varepsilon_{i,t} \tag{1}$$

where $Earnings_{i,t}$ stands for log real earnings, Age_{it} stands for individual age, σ_t is a time-varying shifter, and $\varepsilon_{i,t}$ is the error term[7]. η_i is a strictly exogenous random effect, independent of the covariates (age) for all t. We assume that this latent variable η_i follows a discrete distribution with K support points, $\eta_1, \eta_2, \ldots \eta_K$, with respective probabilities $p_1, p_2, \ldots, p_K$. This approach for modelling latent classes is the same as in Bonhomme and Robin (2009).[8] From the residuals of this preliminary regression, we obtain the Gaussian residual earnings ranks via the following formula:

$$Z_{i,t} = \Phi^{-1}(F_t(\varepsilon_{i,t})) \tag{2}$$

where ε_{it} are the error terms from (1) and $F_t(\cdot)$ is the cross-sectional distribution of these error terms at each date t. Hence, $Z_{it} \sim N(0, 1)$. As far as the initial conditions are concerned, having purified the residuals from the individual-specific unobserved heterogeneity (multiplied by a time shift) before transforming them into Gaussian ranks for the subsequent estimation steps, we can safely assume that Z_{i0} is independent from the unobserved heterogeneity η_i (see Wooldridge (2005)).

[6]We obtain identical test results when considering variance of residual earnings instead of variance of raw hourly earnings, that is, both within and between decile variance of residual earnings statistically significantly decreased in the bottom deciles of the residual earnings distribution after 2015.

[7]Note that σ_t includes indeed a separate time shift for each year, thus allowing aggregate shifts in individual heterogeneity, while there is still a constant time effect and a time-constant individual heterogeneity.

[8]Equation (1) is not estimated with fixed effects, because this would entail a bias due to the incidental parameter problem (Lancaster, 2000) in the estimated second-stage copula parameters (both with the fully parametric and with the semi-nonparametric copula model). In that case, one option would be to correct, at least partially, the bias, by using the method proposed by Fernández-Val and Vella (2011), or that developed by Hahn and Kuersteiner (2011). In the present paper we do not follow this route, but rather we estimate equation (1) via latent classes. Equation (1) is hence essentially the same as equation (1) in Bonhomme and Robin (2009).

In the empirical application, we replace the theoretical residuals ε_{it} with their empirical counterparts, and we obtain the estimated Gaussian ranks[9]:

$$\hat{Z}_{i,t} = \Phi^{-1}(\hat{F}_t(\hat{\varepsilon}_{i,t}))$$

where $\hat{F}_t(\cdot)$ is the estimated counterpart of $F_t(\cdot)$, that is, the empirical cross-sectional distribution of the estimated residuals. This quantity corresponds to the (individual) percentile in the empirical cross-sectional distribution of the residuals. We use the function Φ^{-1} to transform the uniform ranks into their standard Gaussian counterparts for ease of interpretation and mathematical modelling. Equation (1) is estimated separately for the two periods, that is, before and after the introduction of the minimum wage.[10] We do not account for the possible endogeneity of the unemployment patterns, but we present (in Appendix B.3 in the supporting information) a robustness check performed on a subsample of individuals with strong labor market attachment (i.e., males between 25 and 55 years old) who where continuously employed during the period considered. Further, in the wake of Bonhomme and Robin (2009) we assume that the coefficients for age and age squared in equation (1) are the same for all individuals. This means that our model belongs to the family of the restricted income profiles (RIPs) specifications, sharing this feature with, for example, Hryshko (2012) and Arellano et al. (2017).

We now need to model the dynamics of the Gaussian residual earnings ranks Z_{it}. To start with, let us assume that the pair $(Z_{it}, Z_{i,t-1})$ has copula probability density function (pdf) $c(u, v)$ for arguments $u, v \in [0, 1], u = \Phi(Z_{it}), v = \Phi(Z_{i,t-1})$. A copula is a multivariate distribution with standard uniform marginals; it couples marginal distributions to obtain a joint one. Copulas are used to describe the dependence between random variables. Given that we are interested in the dependence structure between the present and the past residual earnings ranks, copulas are a natural choice. Copulas are useful devices, since they allow tackling the modelling of the joint and that of the marginal distributions as separate problems. For a comprehensive survey of copulas and their properties, we refer the reader to Joe (1997) and Nelsen (1999). To simplify the exposition, we abstract for a moment from the presence of individual covariates. We will introduce individual explanatory variables back later. Then, the conditional expected rank is

$$\begin{aligned} E[Z_{it}|Z_{i,t-1}] &= \int_{-\infty}^{\infty} zc(\Phi(z), \Phi(Z_{i,t-1}))\Phi(z)dz \\ &= \int_0^1 \Phi^{-1}(u)c(u, \Phi(Z_{i,t-1}))du, \end{aligned} \tag{3}$$

where Φ is the pdf of the $N(0, 1)$ distribution. This is the formula that we will use in the empirical part for forecasting future ranks given the present rank and the value of the individual covariates. The easiest way to measure rank mobility in this framework is to use a fully parametric copula in equation (3). In the following, we resort to the one-parameter Plackett copula, because it has been used by Bonhomme and Robin (2009). The Plackett copula bivariate cumulative distribution function (cdf) is (Plackett, 1965)

$$C(u, v) \equiv C(u, v; \tau) = \frac{1}{2\tau}\left[1 + \tau(u + v) - a(u, v; \tau)^{1/2}\right], \tag{4}$$

where $a(u, v; \tau) = [1 + \tau(u + v)]^2 - 4\tau(1 + \tau)uv$ and $u, v \in [0, 1], u = \Phi(Z_{it}), v = \Phi(Z_{i,t-1})$. The copula parameter τ is a function of individual covariates (age and education). On the basis of the estimated parameter for the Plackett copula, we can then predict the estimated $\tilde{Z}_{it}$ for each individual in both our pre-reform and post-reform samples, given the value of $Z_{i,t-1}$ and those of the individual covariates, according to the following formula, which is the empirical counterpart of Equation (3):

$$\tilde{Z}_{i,t} = E[Z_{it}|Z_{i,t-1}] = \int_0^1 \Phi^{-1}(u)\hat{c}(u, \Phi(Z_{i,t-1}))du \tag{5}$$

where $\Phi^{-1}(\cdot)$ is the standard normal quantile function, $\Phi(\cdot)$ is the standard normal cdf, and $\hat{c}(\cdot, \cdot) = c(\cdot, \cdot, \hat{\tau})$, that is, the Plackett copula density, whose parameter depends on the individual covariates and has been estimated by

[9]In the empirical part, equation (1) has been estimated with the STATA package gllamm. To construct the estimated residuals, the latent variable η_i is replaced by its empirical Bayes predictions ($\hat{\eta}_i$), which have been obtained via the STATA command gllapred.

[10]Note that this implies that the distribution of permanent earnings heterogeneity is allowed to change after the reform. In Appendix B in the supporting information, we present a robustness check in which equation (1) is estimated on the full sample. Our main results are robust to this check.

maximum likelihood. The integral is computed by Monte Carlo simulation with 1000 simulations. Once we have the predicted residual rank $\tilde{Z}_{i,t}$, we are able to recover the predicted wage via the following formula:

$$\tilde{Earnings}_{i,t} = \hat{\alpha}_1 Age_{it} + \hat{\alpha}_2 Age_{it}^2 + \hat{\sigma}_t \hat{\eta}_i + \hat{F}_{\epsilon,t}^{-1}(\Phi(\tilde{Z}_{i,t})). \quad (6)$$

The relationship between predicted earnings at time t and $Z_{i,t}$ depends on the individual fixed effect η_i multiplied by the time shift σ_t, the observable regressors Age_{it} and Age_{it}^2, and the calendar time t (via the time fixed effect and cdf $F_{\epsilon,t}$). This allows us to construct estimated transition matrices between $Earnings_{i,t-k}$ (recorded in the data) and $\tilde{Earnings}_{it}$ for $k = 1, 2$. We then effectively report all of our results in terms of wage transitions (and not in terms of residual earnings transitions).

Let us now relax the assumption that the copula function is fully parametric. In the wake of Naguib and Gagliardini (2020), we construct a new family of copulas, in which the finite-dimensional parameter is replaced by a functional parameter, which in turn is allowed to depend on covariates. As shown by Naguib and Gagliardini (2020), a flexible nonparametric family of copula functions can be written as follows. Let us consider the nonlinear autoregressive dynamics:

$$Z_{i,t} = \Lambda(\rho(Z_{i,t-1}) + \epsilon_{i,t}) \quad (7)$$

where by hypothesis $\epsilon_{i,t} \sim IIN(0,1)$, Λ is a strictly monotonic increasing function and ρ is a function that expresses the dependence between the past and the present individual ranks. The larger is the value of the partial derivative of the function $\rho(\cdot)$ with respect to the past rank, the higher is the degree of individual positional persistence. Under the condition that $\Lambda(k)$ is such that

$$\Lambda(k) = \Phi^{-1}\left[\int_{-\infty}^{\infty} \Phi(k - \rho(Z_{i,t-1}))\Phi(Z_{i,t-1})dZ_{i,t-1}\right], \quad (8)$$

the invariant distribution of Markov process $(Z_{i,t})$ is $N(0,1)$. Following Naguib and Gagliardini (2020), the copula density of $Z_{i,t}$ and $Z_{i,t-1}$ reads

$$c(u, v; \rho(\cdot)) = \frac{\Phi[\Lambda^{-1}(\Phi^{-1}(u)) - \rho(\Phi^{-1}(v))]}{\Phi(\Phi^{-1}(u))\Lambda(\Lambda^{-1}(\Phi^{-1}(u)))}, \quad (9)$$

for the arguments $u, v \in [0,1]$, $u = \Phi(Z_{it})$, $v = \Phi(Z_{i,t-1})$. This copula family is parametrized by the autoregressive function $\rho(\cdot)$. We now introduce the vector of regressors, $X_{i,t}$ in the functional parameter indexing the copula, which then becomes $\rho(\cdot, X_{i,t})$. This is admissible because essentially any function $\rho(\cdot)$ can be used to parametrize the autoregressive copula. Hence, the copula pdf will be a function of ρ, Λ and $X_{i,t}$. The only requirement on the exogenous process $(X_{i,t})$ is that it is stationary and Markov. On the basis of our estimated semi-nonparametric copula model, we are able to predict the present rank, $\tilde{Z}_{it}$ given the values of $Z_{i,t-1}$ and those of the individual covariates:

$$\tilde{Z}_{it} = \hat{\Lambda}(\hat{\rho}(Z_{i,t-1}, X_{i,t}'\hat{\beta}_2) \quad (10)$$

where $\hat{\Lambda}(k)$ is the estimated function $\Lambda(k)$ which appears in equation (8) and $\hat{\rho}(Z_{i,t-1})$ is the empirical counterpart of function $\rho(Z_{i,t-1})$ in Equation (7). Then, similarly to what we do in the fully parametric case, we are able to predict earnings at time t and to estimate transition matrices between $\tilde{Earnings}_{it}$ and $Earnings_{i,t-1}$, over different time horizons. The estimation procedure consists in three steps (see Appendix A in the supporting information for further details). In the first one, we estimate the preliminary regression (1) and we construct the empirical ranks $\hat{Z}_{it}$ on the basis of the residuals. In the second step, we estimate the conditional marginal distributions of the present and of the past Gaussian ranks, via a kind of Maximum Likelihood procedure. In order to tackle the curse of dimensionality due to the number of regressors, we adopt an index approach; that is, we summarize all the individual covariates by their weighted sum, which is called marginal distribution score or index, and then, we estimate simultaneously the weights of this sum and the marginal rank distributions conditioned on this index. Then, in the third and final step, we estimate the autoregressive function indexing the copula pdf by adopting a Sieve maximum likelihood approach. This autoregressive function $\rho(\cdot;\cdot)$ admits two arguments: the individual past Gaussian rank in the distribution and a second index or score, that is, a weighted sum of individual explanatory variables, whose weights are estimated simultaneously with function ρ itself. We estimate the

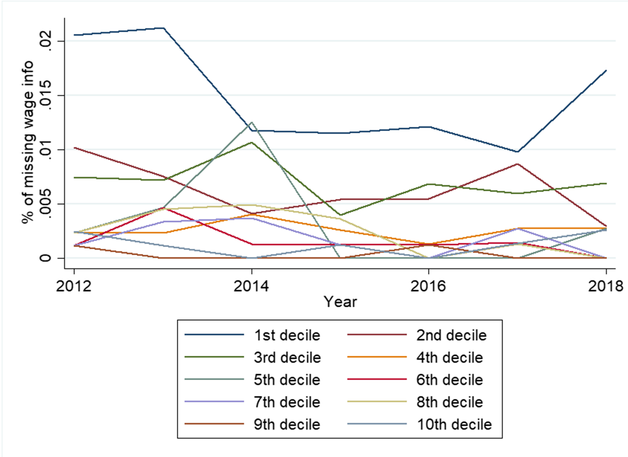


FIGURE 1 Distribution of missing hourly wage information due to panel attrition across previous year hourly wage deciles and years, full sample

function ρ non-parametrically with the method of Sieves. In particular, in our implementation, this autoregressive function is approximated via a bivariate Hermite polynomial basis of degree two. To summarize, the copula function presented in (9) takes here the following form:

$$c(\cdot, \cdot, X_{i,t}) = c(\cdot, \cdot, \rho(\cdot, X'_{i,t}\beta)), \tag{11}$$

where we call the index $W_{it} = \beta' X_{it}$ "mobility score."

3 | THE DATA

The dataset used for analysis is the German Socio Economic Panel (GSOEP). We focus on the years 2011–2018, so that we have a clear pre-reform period (2011–2014) and a clear post-reform period (2015–2018) of equal length. In our main analyses and estimations, we focus on a sample of individuals (both males and females) who are between 16- and 64-year-old. In this way, we make sure to include individuals who are most likely to be affected by the minimum wage, that is, students with temporary jobs, females, some old-age employed individuals, and in general individuals with unstable employment relationships. In Appendix B in the supporting information, as robustness checks, we perform the same analyses and estimations on subsamples of, respectively, men only, women only, and individuals with strong labor attachment only, that is, 25- to 55-year-old males. Our main results are robust to all these different choices of the dataset. Our (unbalanced) dataset used for the main analyses includes 106,970 individual-year observations, whereas the average sample size per year is 13,371. Missing years of data (i.e., non reports) are treated as missing-at-random and dropped.[11] On the other hand, reported zero earnings are treated as individuals being unemployed. These observations are included in the descriptive statistics. However, these observations are excluded from the main model estimations (Section 4). Unemployment rate has been consistently low in Germany in the years considered (ranging from around 7.1% in 2011 to 5.2% in 2018, see also Tables 2 and 3); hence, we deem that transitions into and out of unemployment should not relevantly bias our results on earnings mobility. To be more precise on this point, in the following, we present transition matrices for earnings with and without including a separate zero earnings state. These two sets of matrices are notably similar to each other, as it will be discussed below. Our main variable of interest is individual hourly real earnings, that is, total annual real earnings from wages and salaries of all the jobs of the individual, deflated by the consumer price index and divided by total number of annual hours worked. Self-employed individuals are dropped from the sample. Table 1 reports summary statistics for the main variables before and after the introduction of the minimum wage.

From Table 1, we deduce that average age remained essentially stable in the sample in the period considered. On the other hand, the mean log real hourly wage slightly increased between 2011 and 2018. However, its variance remained essentially unchanged. Similarly to Bonhomme and Robin (2009), we use as explanatory variables age, age squared, and a qualitative variable representing the highest education level achieved by the individual. The five education dummies included in the model correspond to professional middle school, apprenticeship, professional high school, high school

[11]These are observations fully missing from our dataset because of panel attrition. Descriptive statistics about the distribution of missing data is reported in Figure 1. On the other hand, some individuals have missing hourly wage information, but they appear in the dataset under the label "unemployed." Descriptive statistics about individuals self-reporting being unemployed, by year and by previous year earnings decile, are reported in Table 2.

TABLE 1 Data description, by year, full sample, GSOEP data

Men	2011	2012	2013	2014	2015	2016	2017	2018
Age (with zeros)	43.09	41.61	42.47	42.87	42.21	43.25	43.27	43.46
Female dummy	0.5	0.52	0.52	0.51	0.51	0.53	0.52	0.52
Mean log real earn (w/o zeros)	2.58	2.59	2.61	2.63	2.63	2.66	2.68	2.76
Log earn variance (w/o zeros)	0.34	0.33	0.32	0.33	0.35	0.32	0.33	0.29
No. of individuals (with zeros)	10,340	13,689	13,274	13,841	16,773	12,695	13,739	12,619

TABLE 2 Percentage of unemployed individuals by previous data year earnings decile, GSOEP data, full sample, by year

Percentage of unemployed individuals in each year							
Past earn. decile	2012	2013	2014	2015	2016	2017	2018
1	2.05%	2.12%	1.32%	1.15%	1.21%	1.31%	1.73%
2	1.02%	0.76%	0.55%	0.54%	0.55%	1.01%	0.29%
3	0.75%	0.72%	1.07%	0.40%	0.68%	0.75%	0.83%
4	0.24%	0.23%	0.40%	0.26%	0.13%	0.28%	0.28%
5	0.24%	0.47%	1.25%	0.00%	0.13%	0.00%	0.27%
6	0.12%	0.47%	0.13%	0.12%	0.12%	0.14%	0.00%
7	0.12%	0.34%	0.37%	0.12%	0.00%	0.27%	0.00%
8	0.23%	0.45%	0.49%	0.36%	0.00%	0.13%	0.00%
9	0.11%	0.00%	0.00%	0.00%	0.12%	0.00%	0.00%
10	0.24%	0.12%	0.00%	0.12%	0.00%	0.14%	0.39%

TABLE 3 Percentage of zero earnings by previous data year earnings decile, GSOEP data, full sample, by year

Percentage of zero earnings in each year							
Past earn. decile	2012	2013	2014	2015	2016	2017	2018
1	3.97%	4.24%	2.94%	3.01%	2.88%	2.78%	2.60%
2	1.65%	1.01%	0.68%	1.22%	1.37%	1.73%	0.29%
3	1.12%	0.84%	1.20%	0.93%	1.09%	1.04%	0.83%
4	0.48%	0.35%	0.53%	0.39%	0.13%	0.41%	0.28%
5	0.24%	0.47%	1.25%	0.00%	0.25%	0.00%	0.27%
6	0.12%	0.47%	0.13%	0.37%	0.24%	0.28%	0.00%
7	0.35%	0.34%	0.37%	0.37%	0.00%	0.41%	0.00%
8	0.23%	0.45%	0.49%	0.48%	0.00%	0.27%	0.00%
9	0.11%	0.12%	0.12%	0.12%	0.12%	0.00%	0.00%
10	0.24%	0.12%	0.12%	0.24%	0.13%	0.14%	0.39%

diploma, and university (and professional university) degree. We argue that these dummy variables are exogenous; that is, they are not influenced by the individual position in the earnings distribution. Indeed, we only consider education that takes place before labor market entry. Age is included in all three stages of estimation, whereas education is included in the second and in the third stage.

This approach closely resembles the one followed by Bonhomme and Robin (2009). Note that in principle, the same variables can be included in all the three stages of estimation. Indeed, in the preliminary earnings regression, we estimate the role of a certain variable in determining the raw earnings level. On the other hand, in the second step, we estimate the role of the same variable in determining the individual rank in the empirical cross-sectional distribution of the residual earnings. Finally, in the third step, we estimate its role in determining the individual degree of rank persistence or immobility.

In Figure 1, we report the distribution of missing hourly wage information due to panel attrition across years and across previous year hourly wage deciles. From Figure 1, we deduce that there is no clear upward or downward trend in missing wage information across time. In general, missing wage observations range from 0% to 2% of the sample size. Further, as it could be expected, missing wage is more likely at the bottom of previous year's wage distribution. However, differences across deciles are modest, ranging between 1% and zero.

From the left panel of Figure 2, we notice that the distribution of hourly earnings slightly shifted to the right after the introduction of the minimum wage. From the right panel of Figure 2, we find that inequality, as measured by the Gini coefficient, has slightly decreased between 2011 and 2018 (i.e., 0.3 vs. 0.28). This is fully consistent with the idea of minimum wage primarily targeting absolute wage inequality (see Bossler and Schank (2020), and, for the US, David et al., 2016). In Table 2, we report the share of individuals recorded as unemployed in each data year, by their previous

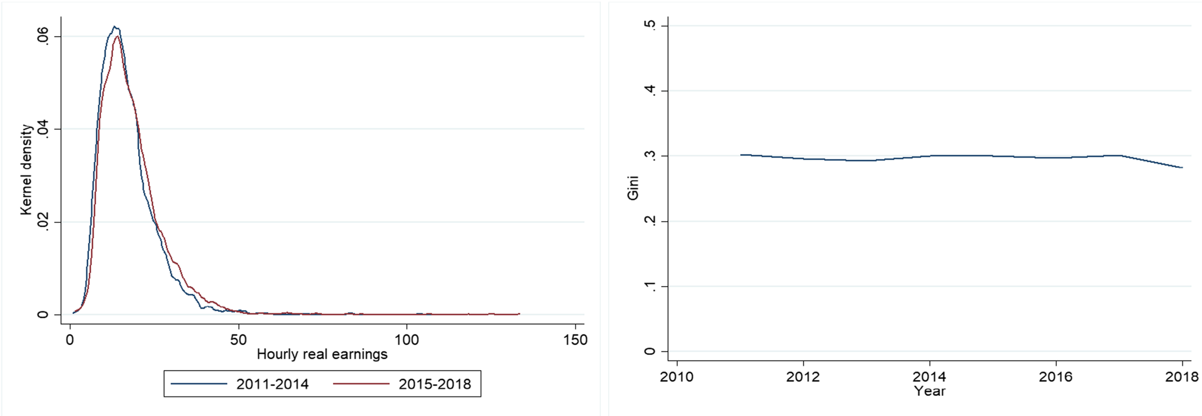
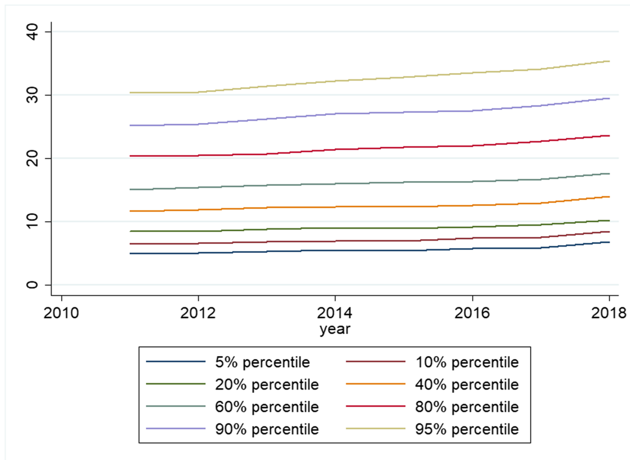


FIGURE 2 Left panel: kernel density estimation of hourly real earnings, by year, GSOEP data, full sample. Right panel: Gini coefficient of hourly real earnings, by year, GSOEP data, full sample

FIGURE 3 Evolution of real hourly wage percentiles, full sample 2011–2018



data year hourly earnings decile. From Table 2, we deduce that the share of unemployed individuals, by previous year's earnings decile, is rather low, ranging between zero and around 2%. Of course, these numbers are so low, because several individuals who are unemployed at year t were also unemployed at year $t-1$. These individuals do not appear in Table 2. Further, from Table 2, we deduce that, as expected, the probability of being unemployed at year t is higher for individuals who were in the first and in the second bottom earnings decile in year $t-1$. On the contrary, the probability of being unemployed in year t is almost zero for individuals who were in the upper earnings deciles in year $t-1$.

In Table 3, we report the share of individuals with zero annual earnings in each data year, by their previous data year earnings decile. The numbers reported in Table 3 essentially coincide with those reported in Table 2, that is, individuals being unemployed. However, in some cells of Table 3, the numbers are slightly higher than in the corresponding cells of Table 2, as some individuals record being employed but earning a wage equal to zero. From this table, we deduce that zero earnings are more common for individuals who where already at the bottom decile of the earnings distribution (the share ranges between around 2.6 and 4.2%). In the other deciles, the share of individuals with zero earnings is moderate, ranging in most cases from 0% to around 1.4% in the years considered in our sample.

From Figure 3, we deduce that real hourly earnings have witnessed an increasing trend in our sample between 2011 and 2018, even after controlling for inflation. The distance between the different percentiles, on the contrary, appears to have remained essentially stable during the period of the analysis.

In Tables 4 and 5, we report actual transition matrices between present and past hourly earnings, over a 1-year and over a 2-year time horizon, before and after the introduction of the national minimum wage. In Tables 4 and 5, we simply drop all individual-year observations recording a zero wage (i.e., we do not require individuals to be continuously employed for a certain period). Transition matrices are one of the most commonly used methods to assess the degree of earnings mobility within an economy (see, e.g., Bonhomme and Robin (2009); Dickens (2000); Fields and Ok (1999); Shorrocks (1978)). When naming data pairs, we always use the latter year. For example, mobility in 2012 means mobility between 2011 and

2012. In these transition matrices, rows stand for past deciles, whereas columns stand for present deciles. The row totals of each matrix are equal to one. For example, the cell in the second row, first column of the upper part of Table 4, means that, among all individuals who were in the second residual earnings decile in period $t-1$ before the reform, around 21% fell in the first (i.e., bottom) residual earnings decile in period t. Conversely, the cell in the first row, second column of the same table signifies that, among all individuals who were in the bottom decile at time $t-1$ before 2015, around 24% ended up in the second decile in period t. In Tables 4 and 5, an individual is recorded as a stayer if he/she is recorded to be in the same residual earnings decile in period $t-1$ and in period t, and a mover otherwise. The percentages of stayers are displayed in bold along the main diagonal of the transition matrix. Of course, a limitation of the transition matrix approach is that all intra-decile transitions are disregarded.

From Table 4, we notice an increase in the degree of earnings persistence at the bottom of the earnings distribution after 2015. Indeed, the share of stayers in the first (bottom) decile increased from around 0.45 to more than 0.5. This change is statistically significant.[12] Such an increase in persistence is explained by small drops (i.e., around one percentage point each) in the shares of those who, starting from the first bottom earnings decile in year t, end up in the second, third, fourth, and fifth earnings deciles in year t + 1 (these shares are, respectively, 0.24 vs. 0.22, 0.12 vs. 0.11, 0.07 vs. 0.06, and 0.04 vs. 0.037). This suggests that minimum wage introduction reduced earnings mobility at the bottom of the earnings distribution.

To be more precise, we witness a decline in upward mobility of minimum wage workers. At the same time, we find indication of a decrease in downward mobility into minimum wage jobs; that is, for example, the share of those falling into the first bottom decile starting from the second decile is equal to around 0.21 before the reform and around 0.18 afterwards (see Table 4). Apart from the increase in earnings persistence in the bottom decile, in the other parts of the distribution, we do not find evidence of relevant changes in the mobility patterns. For example, the share of stayers in the top earnings decile is 0.74 before 2015 and 0.73 after, the difference in these two shares being statistically insignificant.

In all the transition matrices, percentiles computed on the basis of raw hourly earnings are used to construct transitions. These percentiles are re-computed in each data year. In Table 5, we report 2-year transitions for the full sample. From Table 5, we deduce that, consistently with economic theory, persistence is (slightly) lower on a 2-year horizon than on a 1-year horizon. Further, we notice an increase in persistence at the bottom of the distribution after 2015 (0.42 vs. 0.39), as well as an increase in persistence in the second bottom earnings decile (0.36 vs. 0.32).

Overall, from the transition matrices reported in Tables 4 and 5, we deduce that (i) the degree of 1-year positional mobility in the earnings distribution is rather high, with around 50–70% (i.e., 100% minus the average of the numbers reported on the main diagonal of the matrices) of individuals moving earnings decile after 1 year. (ii) In general, we observe more positional persistence at the top and at the bottom of the distribution, that is, in the first and in the tenth earning deciles. Persistence takes hence a U-shape; that is, it is higher at the bottom and at the upper deciles, while it is lower in the middle of the distribution. This is essentially true both before and after 2015 and on both time horizons considered. This finding, that is, more stability at the extremes of the distribution, is consistent with those of, for example, Bonhomme and Robin (2009); Cardoso (2006); Gernandt (2009); Pavlopoulos et al. (2007). (iii) After 2015, we find an increase in positional persistence at the bottom decile. This is more evident over a 1-year time horizon.

In Appendix B in the supporting information, we report the same analyses of Tables 4 and 5 performed, respectively, on a subsample of men only, on a subsample of women only, and on a subsample of individuals with high labor market attachment (i.e., 25- to 55-year-old men continuously employed during the analysis sample). In the following, in order to better understand what happens at the bottom of the raw hourly earnings distribution, we proceed with the exploratory data analysis by producing the 1-year transition matrix in which zero earnings years are not dropped and a separate zero earning state in is included. Indeed, in Table 6, we present the analysis of 1-year transitions between deciles by also including zero earnings as a separate state. For reasons of space, we do not report the same analysis over a 2-year time horizon. From this table, we deduce that, when including zero earnings individual-year observations into the analysis, we still witness an increase in persistence in the bottom first earnings decile after 2015 (the share of stayers jumps from around 45% to around 49%). The size of the jump is comparable to what we find in Table 4, that is, disregarding the zero earnings state.

[12]Please note that, whenever in the present paper a claim is made about statistical significance of a change in recorded shares, this claim is based on the value of t-tests for which the estimated covariance between pre- and post-shares has been used. This estimated covariance has been obtained by bootstrapping 100 times the main estimation procedure and then computing the empirical covariance between the two series of the 100 estimated values pre- and the 100 estimated values post-2015 for each of the cells in the matrix. On this basis, we claim than the drop in mobility in the bottom decile is statistically significant, whereas the recorded change in persistence in the top decile is statistically insignificant.

TABLE 4 Empirical 1-year transition matrices, unbalanced panel (zero earnings dropped)

Origin	Destination 1	2	3	4	5	6	7	8	9	10
2011–2014										
1	**.4543 (.0099)**	.2347 (.0085)	.1217 (.0065)	.068 (.005)	.0434 (.0041)	.0294 (.0034)	.0191 (.0027)	.0115 (.0021)	.0088 (.0019)	.0091 (.0019)
2	.2071 (.0076)	**.3688 (.0091)**	.1954 (.0075)	.0949 (.0055)	.052 (.0042)	.0322 (.0033)	.0205 (.0027)	.0131 (.0021)	.0078 (.0017)	.0081 (.0017)
3	.0949 (.0055)	.2013 (.0075)	**.3333 (.0088)**	.1859 (.0073)	.0802 (.0051)	.0543 (.0042)	.0256 (.003)	.0158 (.0023)	.006 (.0014)	.0028 (9.9e-0.4)
4	.0494 (.004)	.0862 (.0052)	.1911 (.0072)	**.3101 (.0085)**	.1938 (.0073)	.0873 (.0052)	.0426 (.0037)	.0274 (.003)	.0088 (.0017)	.0034 (.0011)
5	.0308 (.0031)	.0385 (.0035)	.0706 (.0047)	.194 (.0072)	**.3128 (.0084)**	.2003 (.0073)	.0859 (.0051)	.0415 (.0036)	.0189 (.0025)	.0066 (.0015)
6	.0179 (.0024)	.0225 (.0027)	.0345 (.0033)	.0821 (.005)	.1885 (.0071)	**.3387 (.0085)**	.1931 (.0071)	.0814 (.0049)	.0306 (.0031)	.0107 (.0019)
7	.0117 (.0019)	.0117 (.0019)	.022 (.0026)	.0409 (.0036)	.0691 (.0046)	.1881 (.007)	**.3518 (.0086)**	.2053 (.0073)	.0756 (.0048)	.024 (.0028)
8	.0063 (.0014)	.0089 (.0017)	.0114 (.0019)	.0228 (.0027)	.0418 (.0036)	.0633 (.0043)	.1959 (.0071)	**.4085 (.0087)**	.2 (.0071)	.0411 (.0035)
9	.0047 (.0012)	.0063 (.0014)	.0066 (.0014)	.0075 (.0015)	.0167 (.0023)	.0264 (.0028)	.0609 (.0042)	.1891 (.0069)	**.5024 (.0089)**	.1794 (.0068)
10	.0084 (.0016)	.0068 (.0015)	.0045 (.0012)	.0071 (.0015)	.0071 (.0015)	.0123 (.002)	.024 (.0028)	.0383 (.0035)	.1562 (.0065)	**.7351 (.008)**
2015–2018										
1	**.5016 (.0108)**	.2235 (.009)	.1115 (.0068)	.0565 (.005)	.0367 (.0041)	.0235 (.0033)	.016 (.0027)	.0108 (.0022)	.008 (.0019)	.0118 (.0023)
2	.1758 (.008)	**.3892 (.102)**	.2225 (.0087)	.0977 (.0062)	.0458 (.0044)	.0292 (.0035)	.0175 (.0027)	.0118 (.0023)	.0057 (.0016)	.0048 (.0014)
3	.0738 (.0054)	.1738 (.0078)	**.3473 (.0098)**	.2072 (.0083)	.0916 (.0059)	.0464 (.0043)	.0295 (.0035)	.011 (.0021)	.0135 (.0024)	.0059 (.0016)
4	.0347 (.0037)	.0664 (.0051)	.1577 (.0074)	**.326 (.0095)**	.2179 (.0084)	.1057 (.0062)	.0504 (.0044)	.0219 (.003)	.0128 (.0023)	.0066 (.0016)
5	.0213 (.0029)	.0333 (.0036)	.0658 (.005)	.1694 (.0075)	**.3348 (.0095)**	.2144 (.0082)	.0988 (.006)	.0397 (.0039)	.0149 (.0024)	.0076 (.0017)
6	.0109 (.0021)	.0234 (.003)	.0339 (.0036)	.0722 (.0052)	.1653 (.0075)	**.3476 (.0096)**	.2173 (.0083)	.0891 (.0057)	.0282 (.0033)	.0121 (.0022)
7	.0087 (.0018)	.0122 (.0022)	.0169 (.0026)	.0351 (.0037)	.0654 (.0049)	.1541 (.0072)	**.3629 (.0095)**	.2533 (.0086)	.0697 (.0051)	.0217 (.0029)
8	.0047 (.0014)	.0082 (.0018)	.0133 (.0023)	.0149 (.0024)	.029 (.0033)	.0706 (.0051)	.174 (.0075)	**.4093 (.0097)**	.2348 (.0084)	.0412 (.0039)
9	.0055 (.0015)	.0051 (.0014)	.0059 (.0015)	.011 (.0021)	.0114 (.0021)	.0302 (.0034)	.064 (.0048)	.1716 (.0075)	**.4955 (.0099)**	.1998 (.0079)
10	.008 (.0018)	.0064 (.0016)	.008 (.0018)	.0084 (.0018)	.0084 (.0018)	.0128 (.0023)	.0253 (.0031)	.0373 (.0038)	.1593 (.0073)	**.7259 (.0089)**

Note: Present decile is on the columns, and past decile is on the rows. Row total is 1. Transitions are computed on the basis of raw hourly earnings.

TABLE 5 Empirical 2-year transition matrices, unbalanced panel (zero earnings dropped)

Origin	Destination 1	2	3	4	5	6	7	8	9	10
2011–2014										
1	**.3902 (.106)**	.2257 (.0091)	.1331 (.0074)	.0827 (.006)	.0621 (.0052)	.0371 (.0041)	.032 (.0038)	.0174 (.0028)	.0113 (.0023)	.0085 (.002)
2	.1895 (.0081)	**.3175 (.0096)**	.21 (.0084)	.1204 (.0067)	.0619 (.005)	.0444 (.0043)	.023 (.0031)	.0154 (.0025)	.0073 (.0018)	.0107 (.0021)
3	.0924 (.0059)	.1823 (.0079)	**.2974 (.0094)**	.1966 (.0081)	.0987 (.0061)	.0575 (.0048)	.0319 (.0036)	.0235 (.0031)	.0143 (.0024)	.0055 (.0015)
4	.0563 (.0046)	.0692 (.0051)	.1541 (.0072)	**.2776 (.009)**	.2116 (.0082)	.1231 (.0066)	.0579 (.0047)	.0282 (.0033)	.0141 (.0024)	.008 (.0018)
5	.0236 (.003)	.0397 (.0039)	.0739 (.0052)	.1721 (.0075)	**.2766 (.0089)**	.2145 (.0081)	.1132 (.0063)	.0538 (.0045)	.0236 (.003)	.009 (.0019)
6	.0198 (.0027)	.0244 (.003)	.0419 (.0039)	.0731 (.0051)	.1721 (.0074)	**.2939 (.0089)**	.2056 (.0079)	.1123 (.0062)	.0426 (.0039)	.0145 (.0023)
7	.0141 (.0023)	.0149 (.0024)	.0183 (.0026)	.0382 (.0037)	.0794 (.0053)	.1747 (.0074)	**.3106 (.009)**	.2346 (.0083)	.0881 (.0055)	.0271 (.0032)
8	.0073 (.0016)	.0149 (.0023)	.0134 (.0022)	.0211 (.0027)	.0283 (.0032)	.0603 (.0045)	.1845 (.0074)	**.3834 (.0093)**	.2309 (.008)	.0559 (.0044)
9	.0033 (.0011)	.004 (.0012)	.0074 (.0016)	.0114 (.002)	.0129 (.0022)	.0261 (.0031)	.0566 (.0044)	.1772 (.0073)	**.4754 (.0096)**	.2257 (.008)
10	.0128 (.0022)	.0086 (.0018)	.0075 (.0017)	.0079 (.0017)	.0075 (.0017)	.0116 (.0021)	.0248 (.003)	.0413 (.0039)	.1634 (.0072)	**.7145 (.0088)**
2015–2018										
1	**.4149 (.0143)**	.2221 (.012)	.1232 (.0095)	.083 (.008)	.0386 (.0056)	.0411 (.0057)	.0268 (.0047)	.021 (.0041)	.0117 (.0031)	.0176 (.0038)
2	.1839 (.0108)	**.3585 (.0134)**	.2097 (.0114)	.1013 (.0084)	.0585 (.0065)	.0351 (.0051)	.0164 (.0035)	.0179 (.0037)	.0094 (.0027)	.0094 (.0027)
3	.0867 (.0077)	.1468 (.0096)	**.2995 (.0125)**	.2135 (.0112)	.1105 (.0085)	.0638 (.0067)	.0445 (.0056)	.0178 (.0036)	.0074 (.0023)	.0096 (.0027)
4	.0295 (.0045)	.0653 (.0065)	.1531 (.0095)	**.2956 (.0121)**	.2121 (.0108)	.1215 (.0087)	.0646 (.0065)	.0323 (.0047)	.019 (.0036)	.007 (.0022)
5	.0232 (.0039)	.0423 (.0053)	.0614 (.0063)	.1515 (.0094)	**.2908 (.0119)**	.2273 (.0109)	.1215 (.0085)	.0526 (.0058)	.0225 (.0039)	.0068 (.0022)
6	.0119 (.0029)	.0307 (.0046)	.0314 (.0046)	.0746 (.0069)	.1506 (.0094)	**.2964 (.0121)**	.2329 (.0112)	.1172 (.0085)	.0397 (.0052)	.0146 (.0032)
7	.0054 (.0019)	.0121 (.0028)	.0201 (.0036)	.0309 (.0045)	.0637 (.0063)	.1549 (.0094)	**.3213 (.0121)**	.2555 (.0113)	.1073 (.008)	.0288 (.0043)
8	.0082 (.0024)	.0089 (.0025)	.0089 (.0025)	.0151 (.0032)	.0411 (.0052)	.0637 (.0064)	.1562 (.0095)	**.3904 (.0128)**	.2514 (.0114)	.0562 (.006)
9	.0047 (.0018)	.0053 (.0019)	.012 (.0028)	.0126 (.0029)	.016 (.0032)	.0333 (.0046)	.0659 (.0064)	.1485 (.0092)	**.4647 (.0129)**	.237 (.011)
10	.0096 (.0026)	.0096 (.0026)	.0082 (.0024)	.0082 (.0024)	.0096 (.0026)	.0179 (.0035)	.0241 (.004)	.0433 (.0053)	.1505 (.0094)	**.7189 (.0118)**

Note: Present decile is on the columns, and past decile is on the rows. Row total is 1. Transitions are computed on the basis of raw hourly earnings.

TABLE 6 Empirical 1-year transition matrices, unbalanced panel (zero earnings included as a separate state)

	Destination										
Origin	**Zero earn**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2011–2014											
Zero earn	**.1477 (.0039)**	.1572 (.004)	.1174 (.0036)	.0985 (.0033)	.0886 (.0031)	.0791 (.003)	.0677 (.0028)	.0657 (.0027)	.057 (.0026)	.0597 (.0026)	.0613 (.0026)
1	.0126 (.0022)	**.4485 (.0099)**	.2317 (.0084)	.1202 (.0064)	.0672 (.005)	.0428 (.004)	.0291 (.0033)	.0189 (.0027)	.0114 (.0021)	.0086 (.0018)	.009 (.0019)
2	.0056 (.0014)	.2059 (.0076)	**.3668 (.009)**	.1943 (.0074)	.0943 (.0055)	.0517 (.0042)	.032 (.0033)	.0204 (.0027)	.013 (.0021)	.0077 (.0016)	.0081 (.0017)
3	.0059 (.0014)	.0943 (.0055)	.2001 (.0075)	**.3314 (.0088)**	.1848 (.0072)	.0797 (.0051)	.054 (.0042)	.0254 (.0029)	.0157 (.0023)	.0059 (.0014)	.0028 (9.8e−0.4)
4	.0024 (8.9e−0.4)	.0493 (.004)	.086 (.0052)	.1906 (.0072)	**.3094 (.0085)**	.1933 (.0073)	.087 (.0052)	.0425 (.0037)	.0273 (.003)	.0088 (.0017)	.0034 (.0011)
5	6.6e−04 (4.7e−0.4)	.0308 (.0031)	.0384 (.0035)	.0706 (.0045)	.1939 (.0072)	**.3126 (.0084)**	.2002 (.0073)	.0858 (.0051)	.0414 (.0036)	.0189 (.0025)	.0066 (.0015)
6	9.8e−04 (5.6e−0.4)	.0179 (.0024)	.0224 (.0027)	.0345 (.0033)	.082 (.0049)	.1884 (.0071)	**.3383 (.0085)**	.1929 (.0071)	.0813 (.0049)	.0306 (.0031)	.0107 (.0019)
7	9.7e−04 (5.6e−0.4)	.0117 (.0019)	.0117 (.0019)	.022 (.0026)	.0408 (.0036)	.069 (.0046)	.1879 (.007)	**.3515 (.0086)**	.2051 (.0073)	.0755 (.0048)	.024 (.0028)
8	.0013 (6.3e−0.4)	.0063 (.0014)	.0088 (.0017)	.0114 (.0019)	.0228 (.0027)	.0417 (.0036)	.0632 (.0043)	.1956 (.0071)	**.408 (.0087)**	.1997 (.0071)	.0411 (.0035)
9	3.1e−04 (3.1e−0.4)	.0047 (.0012)	.0063 (.0014)	.0066 (.0014)	.0075 (.0015)	.0166 (.0023)	.0264 (.0028)	.0609 (.0042)	.1891 (.0069)	**.5022 (.0089)**	.1793 (.0068)
10	.0013 (6.5e−04)	.0084 (.0016)	.0068 (.0015)	.0045 (.0012)	.0071 (.0015)	.0071 (.0015)	.0123 (.002)	.024 (.0028)	.0383 (.0035)	.156 (.0065)	**.7341 (.008)**
2015–2018											
Zero earn	**.1342 (.0024)**	.1152 (.0023)	.1 (.0021)	.0952 (.0021)	.0864 (.002)	.0853 (.002)	.0789 (.0019)	.0763 (.0019)	.0742 (.0019)	.0775 (.0019)	.0768 (.0019)
1	.018 (.0029)	**.4926 (.0107)**	.2195 (.0089)	.1095 (.0067)	.0555 (.0049)	.036 (.004)	.0231 (.0032)	.0157 (.0027)	.0106 (.0022)	.0079 (.0019)	.0116 (.0023)
2	.0074 (.0018)	.1745 (.0079)	**.3863 (.0101)**	.2209 (.0086)	.097 (.0062)	.0455 (.0043)	.029 (.0035)	.0173 (.0027)	.0117 (.0022)	.0056 (.0016)	.0048 (.0014)
3	.0084 (.0019)	.0732 (.0053)	.1724 (.0077)	**.3444 (.0097)**	.2054 (.0083)	.0908 (.0059)	.046 (.0043)	.0293 (.0034)	.0109 (.0021)	.0134 (.0024)	.0059 (.0016)
4	.0029 (.0011)	.0346 (.0037)	.0663 (.005)	.1572 (.0074)	**.3251 (.0095)**	.2173 (.0084)	.1053 (.0062)	.0502 (.0044)	.0218 (.003)	.0128 (.0023)	.0066 (.0016)
5	.0064 (.0016)	.0211 (.0029)	.0331 (.0036)	.0654 (.0049)	.1683 (.0075)	**.3327 (.0094)**	.213 (.0082)	.0981 (.0059)	.0395 (.0039)	.0148 (.0024)	.0076 (.0017)
6	.0024 (9.8e−04)	.0109 (.0021)	.0233 (.003)	.0338 (.0036)	.072 (.0052)	.1649 (.0074)	**.3467 (.0095)**	.2168 (.0083)	.0889 (.0057)	.0282 (.0033)	.0121 (.0022)
7	.0028 (.001)	.0086 (.0018)	.0122 (.0022)	.0169 (.0026)	.035 (.0036)	.0652 (.0049)	.1536 (.0071)	**.3619 (.0095)**	.2527 (.0086)	.0695 (.005)	.0216 (.0029)
8	.0039 (.0012)	.0047 (.0013)	.0082 (.0018)	.0133 (.0023)	.0148 (.0024)	.0289 (.0033)	.0703 (.0051)	.1734 (.0075)	**.4077 (.0097)**	.2339 (.0084)	.041 (.0039)
9	3.9e−04 (3.9e−04)	.0055 (.0015)	.0051 (.0014)	.0059 (.0015)	.011 (.0021)	.0114 (.0021)	.0302 (.0034)	.064 (.0048)	.1715 (.0075)	**.4953 (.0099)**	.1998 (.0079)
10	.0012 (6.9e−04)	.008 (.0018)	.0064 (.0016)	.008 (.0018)	.0084 (.0018)	.0084 (.0018)	.0128 (.0023)	.0253 (.0031)	.0373 (.0038)	.1591 (.0073)	**.7251 (.0089)**

Note: Present decile is on the columns, and past decile is on the rows. Row total is 1. Transitions are computed on the basis of raw hourly earnings.

As far as the influence of minimum wage on (un-)employment is concerned, the introduction of a minimum wage may increase the reservation wages of those looking for jobs in certain sectors and hence raise the wages that employers must pay in those sectors to recruit (Falk et al., 2006; Stewart, 2012). As the minimum wage not only increases wages but also reservation wages, firms may reduce employment (Falk et al., 2006). However, according to Brown et al. (2014), "low" minimum wages (i.e., close enough to what would be the prevailing wage without government intervention) have negligible or even positive employment effect, whereas "high" minimum wages destroy jobs.[13] There is still no consensus among economists about the employment effect of a minimum wage (see, e.g., Flinn (2006); Manning (2021)). As far as the case of Germany is concerned, only moderate negative effects on overall employment have been found (see, e.g., Ahlfeldt et al. (2018); Bossler and Gerner (2020); Caliendo et al. (2018, 2019); Dustmann et al. (2022); Garloff (2019)[14]).

With reference to the theoretical channels mentioned in Section 1, the introduction of a minimum wage may increase job search effort exerted by unemployed individuals and hence lead to an increase in the share of those who leave the zero earnings state. However, since firms may want to substitute low-skilled workers with high skilled workers, we may also witness an increase in entry into unemployment (that we proxy here with the zero earnings state) from the first bottom decile.[15] Empirically, from Table 6, we find slight increases in the shares of those who leave the zero earnings state to reach the middle and upper deciles (i.e., from the fifth upwards: 0.09 vs. 0.08, 0.08 vs. 0.07, 0.07 vs. 0.06, 0.08 vs. 0.06, and 0.08 vs. 0.06), whereas entry in unemployment from the first bottom earnings decile is essentially unchanged (1.8% after vs. 1.3% before, and the difference is not statistically significant). It seems that minimum wage actually increased unemployed workers' incentives for job search and created better matches and surplus. To summarize, we find evidence of an increase in exit from unemployment (that we proxy with the zero earnings state) and essentially no change in entry into unemployment. As far as overall unemployment is concerned, we agree with previous studies on the German case (i.e., Bossler and Gerner, (2020); Caliendo et al. (2018); Dustmann et al. (2022)), which find an essentially zero (or slightly negative) impact of the minimum wage introduction on overall employment. This can be seen, for example, from Table 2, where we notice that the share of individuals recorded as being unemployed, by previous year earnings decile, remained essentially stable after 2015 up to 2018. Moreover, by comparing Table 4 and Table 6, we notice that recorded earnings decile transitions are not very different when including and when excluding zero earnings years. This finding supports the hypothesis that the distortion in our results presented in Section 4 due to disregarding transitions into and out of unemployment should be moderate.

In Appendix B in the supporting information, as robustness checks, we present the same descriptive analyses for a subsample of men, one of women and one of individuals with high labor market attachment. In all these three cases, our main empirical findings are confirmed. There is an increase in persistence at the bottom of the distribution after the reform (43% vs. 49% for men, 46% vs. 51% for women, and 43% vs. 49% in the high labor market attachment sample), whereas the other shares in the transition matrix remain essentially unchanged. Further, when performing the analysis with a separate zero earnings state, we notice that the finding of an increase in upward mobility out of the zero earnings state towards the middle and upper earnings decile is confirmed for men (see Table 15 in Appendix B in the supporting information), whereas it is far less evident from women (see Table 19 in the supporting information). In the following section, we compare the empirical transition matrices presented here with those estimated via the two copula models presented in Section 2, that is, the parametric and the semi-nonparametric ones.

4 | RESULTS AND COMMENTS

In this section, we report and compare the estimation results obtained via the parametric and the semi-nonparametric copula models. All the estimates presented in this section have been obtained on the full sample described in Section 3. As mentioned above, robustness checks results are reported entirely in Appendix B in the supporting information. Note that all results presented in this Section are expressed in terms of hourly wages and hourly wages deciles, in order to be consistent with the descriptive evidence presented in Section 3. Let us consider the results from the fully parametric model first. From Tables 7 and 8, we can assess the fit of the parametric model to the data. For example, the predicted percentage of stayers at the bottom of the residual earnings distribution over a 1-year horizon is around 0.47 before the reform. In the data (Tables 4 and 5), this percentage computed on the basis of actual transitions is 0.45. Further, the predicted shares of

[13] Lee and Saez (2012) develop a theoretical model to identify the optimal minimum wage policy in competitive labor markets.

[14] Note however that Garloff (2019) only focuses on the immediate effect of the minimum wage introduction on employment in year 2015.

[15] Even if, as explained above, this second effect should be more an "immediate" impact rather than a permanent change.

stayers (i.e., individuals on the main diagonals) in the middle deciles range between 0.30 and 0.50, whereas from actual transitions these shares range between 0.31 and 0.50, so the fit of the model is quite good. Table 7 documents the increase in persistence at the bottom of the wage distribution after the introduction of the minimum wage (0.52 vs. 0.47).

This increase is driven by a decrease in upward mobility of minimum wage workers. Indeed, the numbers of those who jump from the first decile to upper deciles are lower after 2015 (0.21 vs. 0.23 to the second decile, 0.12 vs. 0.13 to the third, and so on). On the other hand, from Table 7, we deduce that the fully parametric model fails at predicting the decrease in downward mobility from the second to the first bottom earnings decile that we record in the data. Indeed, in Table 7, the share of those who started in the second decile and fall into the first after 1 year is 0.19 both before and after minimum wage introduction, whereas in Table 4 (actual data), it drops from 0.21 to around 0.18.

Let us consider the prediction accuracy of the fully parametric model over a 2-year horizon. From Table 8, we deduce that the predicted share of stayers in the top residual earnings decile is around 0.72, both before and after the reform. In actual data (Table 5), we also record shares of stayers at the top equal to around 0.72, that is, almost identical to the prediction, both before and after 2015. Also over the 2-year horizon, we find evidence of an increase in persistence at the bottom of the residual earnings distribution (0.43 vs. 0.40). This is broadly consistent with the increase in persistence at the bottom recorded in actual transitions (Table 5: 0.42 vs. 0.39).

Let us now discuss the estimation results of the semi-nonparametric copula model. One main finding emerges: Both the parametric and the semi-nonparametric model correctly predict the main change in mobility patters after 2015, that is, the increase in persistence at the bottom decile. From Tables 9 and 10, we find evidence that the semi-nonparametric copula model has a rather good fit to the data. Indeed, for example, the predicted shares of stayers at the bottom of the residual earnings distribution over a 1-year horizon are 0.46 (pre-reform) and 0.49 (post-reform), whereas the actual ones (reported in Tables 4 and 5) are 0.45 pre reform and 0.5 post reform (the parametric copula model predicts 0.47 pre reform and 0.52 post reform instead). Further, the predicted percentage of stayers at the top of the distribution over the same horizon is 0.73 both before and after the reform versus the actual recorded values of 0.74 pre-reform and 0.73 post-reform. The percentage of stayers over a 1-year horizon ranges between 0.31 and 0.50, which is also in line with actual transitions recorded in the data. On a 2-year horizon, the predicted share of stayers at the bottom of the distribution is 0.39 both before and after the reform, whereas in the data we find, respectively, 0.39 and 0.42.

As robustness checks, in Appendix B in the supporting information, we repeat both the parametric and the semi-nonparametric estimations on a subsample of men, on a subsample of women and on subsample of individuals with high labor market attachment (i.e., 25- to 55-year-old men). We report this analysis over a 1-year time horizon only, for reasons of space. Our main estimation results are confirmed: in the subsample of men, both the parametric and the semi-nonparametric model correctly identify the increase in persistence at the bottom of the distribution (43% vs. 53% with the parametric model, 45% vs. 46% with the semi-nonparametric model), whereas the other cells remain essentially unchanged. The fully parametric model overestimates the drop in mobility at the bottom, whereas the semi-nonparametric model underestimates it in this case (in the data for the subsample of men we record an increase in the share of stayers in the bottom decile from 43% to 49%). As far as the subsample of women is concerned, the fully parametric model predicts an increase from 48% to around 53% of stayers in the bottom earnings decile after 2015, whereas the semi-nonparametric copula predicts an increase from around 47% to more than 51%. In the data, we witness a jump from 46% to around 51%, so also in this case, the semi-nonparametric model has better predictive performance than the fully parametric one.

When analyzing estimation results on our subsample of individuals with high labor market attachment, the same findings are confirmed. Indeed, on this sample as well, the parametric copula correctly predicts an increase in persistence at the bottom of the wage distribution (54% vs. 44%). The semi-nonparametric copula also predicts an increase in persistence in the bottom decile, that is, from 46% to 45% (in actual data, we have 49% vs. 43%). As noticed before in the sample of women, the fully parametric copula tends to overestimate the jump in persistence at the bottom, whereas the fully parametric copula underestimates it.

Finally, as a last robustness check, in Appendix B.3.4 in the supporting information, we estimate again our parametric and semi-nonparametric models on the full sample. The only difference with our main estimation results presented in this Section is that now we estimate the preliminary regression (1) on the full pooled sample, instead of dividing it preliminarily into a pre-reform and a post-reform period. Our main findings are robust to this last check as well. With the parametric copula, we record a jump in persistence in the bottom earnings decile from 44% to around 51%, whereas with the semi-nonparametric model the recorded jump is from 45% to 51%. Also in this case, like in all the previous ones (i.e., subsamples of men, women and 25- to 55-year-old men continuously employed during the period of analysis), the increase

TABLE 7 Parametric copula, 1-year transition matrices

Origin	Destination 1	2	3	4	5	6	7	8	9	10
2011–2014										
1	**.4654 (.0182)**	.2261 (.0153)	.1277 (.0122)	.0559 (.0084)	.0505 (.008)	.0266 (.0059)	.0199 (.0051)	.0173 (.0048)	.0066 (.003)	.004 (.0023)
2	.1934 (.0135)	**.3787 (.0166)**	.1829 (.0132)	.0926 (.0099)	.0563 (.0079)	.0422 (.0069)	.0211 (.0049)	.0188 (.0046)	.0059 (.0026)	.0082 (.0031)
3	.0936 (.0098)	.2158 (.0139)	**.3253 (.0158)**	.1781 (.0129)	.089 (.0096)	.0468 (.0071)	.0194 (.0047)	.0205 (.0048)	.0091 (.0032)	.0023 (.0016)
4	.0442 (.0069)	.0964 (.0099)	.1984 (.0134)	**.3005 (.0154)**	.1848 (.0131)	.0873 (.0095)	.0408 (.0067)	.0363 (.0063)	.0091 (.0063)	.0023 (.0016)
5	.0251 (.0053)	.0389 (.0065)	.0709 (.0087)	.1989 (.0135)	**.3074 (.0156)**	.2046 (.0136)	.0811 (.0092)	.0491 (.0073)	.0171 (.0044)	.0069 (.0028)
6	.016 (.0041)	.0171 (.0042)	.0289 (.0055)	.0845 (.0091)	.1679 (.0122)	**.3497 (.0156)**	.2139 (.0134)	.0824 (.009)	.031 (.0057)	.0086 (.003)
7	.0129 (.0037)	.0172 (.0043)	.0258 (.0052)	.0408 (.0065)	.0687 (.0083)	.1749 (.0124)	**.3648 (.0158)**	.2006 (.0131)	.0665 (.0082)	.0279 (.0054)
8	.0073 (.0027)	.0104 (.0033)	.0073 (.0027)	.0166 (.0041)	.0479 (.0069)	.0749 (.0085)	.1915 (.0127)	**.4142 (.0159)**	.1915 (.0127)	.0385 (.0062)
9	.006 (.0025)	.006 (.0025)	.008 (.0028)	.007 (.0026)	.0121 (.0035)	.0322 (.0056)	.0583 (.0074)	.1859 (.0123)	**.4965 (.0159)**	.1879 (.0124)
10	.0127 (.0036)	.0116 (.0035)	.0053 (.0024)	.0063 (.0026)	.0053 (.0024)	.0095 (.0031)	.0232 (.0049)	.0306 (.0056)	.1688 (.0122)	**.7268 (.0145)**
2015–2018										
1	**.5226 (.0194)**	.2063 (.0157)	.116 (.0124)	.0557 (.0089)	.0407 (.0077)	.0181 (.0052)	.0105 (.004)	.0151 (.0047)	.009 (.0037)	.006 (.003)
2	.1903 (.0148)	**.3949 (.0184)**	.2244 (.0157)	.0852 (.0105)	.0369 (.0071)	.0313 (.0066)	.0185 (.0051)	.0099 (.0037)	.0043 (.0025)	.0043 (.0025)
3	.0717 (.0098)	.1693 (.0142)	**.3572 (.00182)**	.2152 (.0156)	.0689 (.0096)	.0445 (.0078)	.033 (.0068)	.0143 (.0045)	.0172 (.0049)	.0086 (.0035)
4	.0344 (.0068)	.0702 (.0095)	.1444 (.013)	**.3425 (.0176)**	.2228 (.0154)	.1004 (.0111)	.0454 (.0077)	.0193 (.0051)	.0151 (.0045)	.0055 (.0027)
5	.0245 (.0057)	.0231 (.0055)	.0611 (.0088)	.1902 (.0145)	**.3261 (.0173)**	.2133 (.0151)	.091 (.0106)	.0503 (.0081)	.0095 (.0036)	.0109 (.0038)
6	.0085 (.0035)	.0255 (.0059)	.034 (.0068)	.0737 (.0098)	.1445 (.0132)	**.3399 (.0178)**	.2266 (.0158)	.0992 (.0112)	.0312 (.0065)	.017 (.0049)
7	.0116 (.0039)	.0142 (.0043)	.0246 (.0056)	.0401 (.0071)	.066 (.0089)	.1449 (.0127)	**.3648 (.0173)**	.2445 (.0155)	.0737 (.0094)	.0155 (.0044)
8	.0064 (.0029)	.0103 (.0036)	.0103 (.0036)	.0154 (.0044)	.0218 (0052)	.0654 (.0089)	.1795 (.0137)	**.4013 (.0176)**	.2385 (.0153)	.0513 (.0079)
9	.0053 (.0026)	.0053 (.0026)	.0053 (.0026)	.0093 (.0035)	.0119 (.004)	.0318 (.0064)	.0636 (.0089)	.1603 (.0134)	**.4848 (.0182)**	.2225 (.0151)
10	.0079 (.0032)	.0066 (.0029)	.0066 (.0029)	.0092 (.0035)	.0079 (.0032)	.0053 (.0026)	.0317 (.0064)	.0396 (.0071)	.1598 (.0133)	**.7252(.0089)**

Note: Present decile is on the columns, past decile is on the rows. Row total is 1. Transitions between past hourly wage and present wage predicted according to equation (6) are shown. Standard errors have been obtained by bootstrapping.

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TABLE 8 Parametric copula, 2-year transition matrices. Present decile is on the columns, past decile is on the rows. Row total is 1

	Destination									
Orgin	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2011–2014										
1	**.3987 (.0195)**	.2073 (.0161)	.1392 (.0138)	.0728 (.0103)	.068 (.01)	.0427 (.008)	.0364 (.0074)	.0158 (.005)	.0111 (.0042)	.0079 (.0035)
2	.1849 (.0146)	**.3272 (.0177)**	.2063 (.0153)	.111 (.0118)	.0597 (.0089)	.0569 (.0087)	.0299 (.0064)	.0171 (.0049)	.0028 (.002)	.0043 (.0025)
3	.0955 (.011)	.2065 (.0152)	**.2795 (.0168)**	.1784 (.0143)	.0969 (.0111)	.0562 (.0086)	.0393 (.0073)	.0267 (.006)	.0154 (.0046)	.0056 (.0028)
4	.0533 (.0082)	.0626 (.0088)	.1478 (.013)	**.277 (.0163)**	.213 (.0149)	.1185 (.0118)	.0732 (.0095)	.028 (.006)	.0173 (.0048)	.0093 (.0035)
5	.0239 (.0056)	.0465 (.0077)	.0677 (.0092)	.1753 (.0139)	**.2683 (.0161)**	.2045 (.0147)	.1222 (.0119)	.0624 (.0088)	.0199 (.0051)	.0093 (.0035)
6	.0163 (.0045)	.0301 (.006)	.0363 (.0066)	.0852 (.0099)	.1541 (.0128)	**.287 (.016)**	.2118 (.0145)	.1216 (.0116)	.0439 (.0072)	.0138 (.0041)
7	.0087 (.0033)	.0173 (.0046)	.0149 (.0043)	.0347 (.0064)	.0967 (.0104)	.1809 (.0136)	**.2937 (.016)**	.2441 (.0151)	.0855 (.0098)	.0235 (.0053)
8	.0074 (.003)	.0136 (.0041)	.0124 (.0039)	.0186 (.0048)	.0273 (.0057)	.0743 (.0092)	.1846 (.0137)	**.3866 (.0171)**	.223 (.0147)	.052 (.0078)
9	.0035 (.002)	.007 (.0028)	.0082 (.0031)	.0058 (.0026)	.014 (.004)	.0338 (.0062)	.0548 (.0078)	.1832 (.0132)	**.4749 (.0171)**	.2147 (.014)
10	.0136 (.0041)	.0136 (.0041)	.0062 (.0028)	.0074 (.003)	.0086 (.0033)	.0099 (.0035)	.0259 (.0056)	.0309 (.0061)	.1679 (.0131)	**.716 (.0158)**
2015–2018										
1	**.4258 (.0259)**	.228 (.022)	.1484 (.0186)	.0632 (.0128)	.0385 (.0101)	.0275 (.0086)	.022 (.0077)	.0137 (.0061)	.011 (.0055)	.022 (.0077)
2	.2037 (.0207)	**.373 (.0249)**	.2063 (.0208)	.1138 (.0163)	.037 (.0097)	.0238 (.0078)	.0079 (.0046)	.0185 (.0069)	.0053 (.0037)	.0106 (.0053)
3	.0755 (.0135)	.1667 (.019)	**.3073 (.0235)**	.2031 (.0205)	.1276 (.017)	.0677 (.0128)	.0313 (.0089)	.013 (.0058)	.0052 (.0037)	.0026 (.0026)
4	.0378 (.0096)	.0579 (.0117)	.1662 (.0187)	**.3224 (.0235)**	.204 (.0202)	.1008 (.0151)	.0554 (.0115)	.0252 (.0079)	.0277 (.0082)	.0025 (.0025)
5	.0194 (.0068)	.0364 (.0092)	.0704 (.0126)	.1699 (.0185)	**.2403 (.0211)**	.2524 (.0214)	.1165 (.0158)	.068 (.0124)	.0218 (.0072)	.0049 (.0034)
6	.0114 (.0051)	.0319 (.0084)	.0319 (.0084)	.0934 (.0139)	.1617 (.0176)	**.2916 (.0217)**	.2073 (.0193)	.1207 (.0156)	.0319 (.0084)	.0182 (.0064)
7	.0089 (.0044)	.0089 (.0044)	.0177 (.0062)	.0355 (.0087)	.0687 (.0119)	.1353 (.0161)	**.3304 (.0222)**	.2461 (.0203)	.1109 (.0148)	.0377 (.009)
8	.007 (.004)	.0093 (.0046)	.0023 (.0023)	.0117 (.0052)	.0373 (.0091)	.0676 (.0121)	.1748 (.0183)	**.359 (.0232)**	.2541 (.021)	.0769 (.0129)
9	.002 (.002)	.0061 (.0035)	.0143 (.0054)	.0102 (.0046)	.0164 (.0057)	.0348 (.0083)	.0676 (.0114)	.1414 (.0158)	**.4549 (.0225)**	.252 (.0197)
10	.0136 (.0055)	.0113 (.005)	0 (1.7e-06)	.009 (.0045)	.009 (.0045)	.0158 (.0059)	.0317 (.0083)	.0475 (.0101)	.1471 (.0168)	**.7149 (.0215)**

Note: Transitions between past hourly wage and present wage predicted according to equation (6) are shown. Standard errors have been obtained by bootstrapping.

TABLE 9 Semi-nonparametric copula, 1-year transition matrices. Present decile is on the columns, past decile is on the rows

	Destination									
Origin	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2011–2014										
1	**.4615 (.0.128)**	.2262 (.0107)	.1256 (.0085)	.0644 (.0063)	.0401 (.005)	.0296 (.0043)	.0197 (.0036)	.0151 (.0031)	.0092 (.0024)	.0085 (.0024)
2	.2033 (.0098)	**.3636 (.0118)**	.1908 (.0096)	.0957 (.0072)	.0574 (.0057)	.0365 (.0046)	.0209 (.0035)	.0161 (.0031)	.009 (.0023)	.0066 (.002)
3	.0964 (.0071)	.2009 (.0097)	**.3259 (.0113)**	.1857 (.0094)	.0864 (.0068)	.0549 (.0055)	.0245 (.0037)	.0152 (.003)	.007 (.002)	.0029 (.0013)
4	.0468 (.005)	.0879 (.0067)	.1917 (.0093)	**.3106 (.011)**	.1911 (.0093)	.0885 (.0067)	.0383 (.0046)	.0333 (.0043)	.0085 (.0022)	.0034 (.0014)
5	.0275 (.0039)	.0359 (.0044)	.0673 (.0059)	.1985 (.0094)	**.3057 (.0109)**	.2064 (.0096)	.0852 (.0066)	.0454 (.0049)	.0208 (.0034)	.0073 (.002)
6	.0165 (.0029)	.0208 (.0033)	.0367 (.0043)	.0831 (.0064)	.1842 (.0089)	**.3392 (.0109)**	.1954 (.0092)	.0868 (.0065)	.0288 (.0039)	.0085 (.0021)
7	.0106 (.0024)	.0139 (.0028)	.025 (.0037)	.0389 (.0046)	.0712 (.0061)	.1862 (.0092)	**.348 (.0112)**	.2118 (.0096)	.0695 (.006)	.025 (.0037)
8	.0073 (.0019)	.0078 (.002)	.0084 (.0021)	.0262 (.0036)	.0486 (.0049)	.0664 (.0057)	.1867 (.0089)	**.4085 (.0112)**	.1961 (.0091)	.0439 (.0091)
9	.0057 (.0017)	.0062 (.0018)	.0078 (.002)	.0083 (.0021)	.0124 (.0025)	.0295 (.0038)	.059 (.0054)	.1837 (.0088)	**.5026 (.0114)**	.1848 (.0088)
10	.01 (.0023)	.0068 (.0019)	.0042 (.0015)	.0042 (.0015)	.0084 (.0021)	.0105 (.0023)	.0257 (.0036)	.0399 (.0045)	.157 (.0083)	**.7333 (.0101)**
2015–2018										
1	**.4898 (.014)**	.2222 (.0116)	.126 (.0093)	.0548 (.0064)	.0415 (.0056)	.0235 (.0042)	.0117 (.003)	.0133 (.0032)	.007 (.0023)	.0102 (.0028)
2	.1849 (.0104)	**.3821 (.013)**	.2237 (.0112)	.0982 (.008)	.0452 (.0056)	.0244 (.0041)	.0201 (.0038)	.0108 (.0028)	.005 (.0019)	.0057 (.002)
3	.0721 (.0069)	.1784 (.0102)	**.3612 (.0128)**	.1949 (.0106)	.0871 (.0075)	.0443 (.0055)	.03 (.0046)	.0136 (.0031)	.0121 (.0029)	.0064 (.0021)
4	.0302 (.0044)	.0685 (.0065)	.1558 (.0094)	**.3345 (.0122)**	.2129 (.0106)	.1068 (.008)	.051 (.0057)	.0215 (.0038)	.0154 (.0032)	.0034 (.0015)
5	.0218 (.0038)	.0293 (.0044)	.064 (.0064)	.1778 (.01)	**.3243 (.0122)**	.218 (.0108)	.0988 (.0078)	.0463 (.0055)	.0116 (.0028)	.0082 (.0024)
6	.0069 (.0022)	.0261 (.0042)	.0364 (.0049)	.0728 (.0068)	.1662 (.0098)	**.3537 (.0125)**	.2047 (.0106)	.092 (.0076)	.0295 (.0044)	.0117 (.0028)
7	.0097 (.0025)	.0123 (.0028)	.0219 (.0037)	.0368 (.0048)	.0671 (.0064)	.1549 (.0092)	**.3551 (.0122)**	.2544 (.0111)	.0717 (.0066)	.0161 (.0032)
8	.0052 (.0018)	.0091 (.0024)	.0117 (.0027)	.0136 (.0029)	.0272 (.0041)	.068 (.0064)	.1763 (.0097)	**.4161 (.0125)**	.2281 (.0107)	.0447 (.0053)
9	.0064 (.002)	.0051 (.0018)	.0038 (.0016)	.0115 (.0027)	.0115 (.0027)	.032 (.0045)	.0634 (.0062)	.1671 (.0094)	**.4936 (.0127)**	.2055 (.0102)
10	.0061 (.002)	.0054 (.0019)	.0068 (.0021)	.0081 (.0023)	.0088 (.0024)	.0136 (.003)	.0278 (.0043)	.038 (.005)	.1588 (.0095)	**.7266 (.0116)**

Note: Row total is 1. Transitions between past hourly wage and present wage predicted according to Equation (6) are shown. Standard errors have been obtained by bootstrapping.

TABLE 10 Semi-nonparametric copula, 2-year transition matrices. Present decile is on the columns, past decile is on the rows

	Destination									
Origin	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2011–2014										
1	**.3944 (.0137)**	.2121 (.0114)	.1408 (.0097)	.0712 (.0072)	.0681 (.007)	.0407 (.0055)	.0352 (.0052)	.0196 (.0039)	.0094 (.0027)	.0086 (.0026)
2	.1918 (.0105)	**.3171 (.0125)**	.204 (.0108)	.1246 (.0088)	.0623 (.0065)	.048 (.0057)	.0243 (.0041)	.0157 (.0033)	.0064 (.0021)	.0057 (.002)
3	.0872 (.0075)	.183 (.0103)	**.2945 (.0122)**	.1887 (.0105)	.1065 (.0082)	.0593 (.0063)	.0357 (.005)	.0257 (.0042)	.0129 (.003)	.0064 (.0021)
4	.0535 (.0059)	.0623 (.0063)	.1503 (.0093)	**.2877 (.0118)**	.2139 (.0107)	.1219 (.0085)	.0684 (.0066)	.0217 (.0038)	.0135 (.003)	.0068 (.0021)
5	.0212 (.0037)	.0411 (.0051)	.0762 (.0068)	.175 (.0098)	**.2697 (.0114)**	.2187 (.0106)	.108 (.008)	.0603 (.0061)	.0205 (.0037)	.0093 (.0025)
6	.0173 (.0033)	.0281 (.0042)	.0416 (.005)	.0774 (.0068)	.1752 (.0096)	**.289 (.0115)**	.1912 (.0099)	.1202 (.0082)	.0454 (.0053)	.0147 (.003)
7	.0101 (.0025)	.0163 (.0032)	.0151 (.0031)	.0396 (.0049)	.0791 (.0068)	.1828 (.0097)	**.3021 (.0115)**	.2481 (.0108)	.0842 (.007)	.0226 (.0037)
8	.0093 (.0024)	.0142 (.0029)	.0105 (.0025)	.0204 (.0035)	.0297 (.0042)	.0667 (.0062)	.1842 (.0096)	**.3807 (.0121)**	.2293 (.0105)	.055 (.0057)
9	.0036 (.0015)	.0036 (.0015)	.0066 (.002)	.0102 (.0025)	.0168 (.0031)	.0294 (.0041)	.0563 (.0056)	.1774 (.0093)	**.4703 (.0122)**	.2259 (.0102)
10	.0116 (.0027)	.008 (.0022)	.0067 (.002)	.0067 (.002)	.008 (.0022)	.0098 (.0024)	.0233 (.0037)	.0399 (.0048)	.1582 (.009)	**.7278 (.011)**
2015–2018										
1	**.39 (.0181)**	.2268 (.0156)	.1466 (.0132)	.0816 (.0102)	.0415 (.0074)	.0373 (.0071)	.029 (.0062)	.0207 (.0053)	.0124 (.0041)	.0138 (.0043)
2	.1809 (.0138)	**.3773 (.0174)**	.2158 (.0148)	.1072 (.0111)	.0452 (.0075)	.0284 (.006)	.0116 (.0039)	.0168 (.0046)	.0078 (.0032)	.009 (.0034)
3	.0973 (.0105)	.1492 (.0127)	**.3009 (.0163)**	.1985 (.0142)	.1176 (.0115)	.0657 (.0088)	.043 (.0072)	.0126 (.004)	.0101 (.0036)	.0051 (.0025)
4	.0333 (.0062)	.0618 (.0083)	.1474 (.0122)	**.3044 (.0159)**	.2152 (.0142)	.126 (.0114)	.0666 (.0086)	.019 (.0047)	.0226 (.0051)	.0036 (.0021)
5	.0173 (.0044)	.0405 (.0067)	.0705 (.0087)	.1549 (.0123)	**.2601 (.0149)**	.2474 (.0147)	.1179 (.011)	.0636 (.0083)	.0185 (.0046)	.0092 (.0033)
6	.0082 (.0031)	.0294 (.0058)	.0294 (.0058)	.0858 (.0096)	.1622 (.0126)	**.302 (.0157)**	.2197 (.0142)	.1128 (.0108)	.0364 (.0064)	.0141 (.004)
7	.0046 (.0023)	.0125 (.0037)	.0182 (.0045)	.0296 (.0057)	.066 (.0084)	.149 (.012)	**.3231 (.0158)**	.256 (.0147)	.1149 (.0108)	.0262 (.0054)
8	.0056 (.0025)	.009 (.0032)	.0067 (.0027)	.0123 (.0037)	.0392 (.0065)	.0661 (.0083)	.1581 (.0122)	**.3969 (.0164)**	.2489 (.0145)	.0572 (.0078)
9	.0021 (.0015)	.0053 (.0024)	.0138 (.0038)	.0117 (.0035)	.0149 (.0039)	.034 (.0059)	.0722 (.0084)	.1465 (.0115)	**.4554 (.0162)**	.2442 (.014)
10	.0129 (.0038)	.0093 (.0033)	.0047 (.0023)	.007 (.0029)	.0082 (.0031)	.0187 (.0046)	.028 (.0056)	.0409 (.0068)	.1554 (.0124)	**.715 (.0154)**

Note: Row total is 1. Transitions between past hourly wage and present wage predicted according to Equation (6) are shown. Standard errors have been obtained by bootstrapping.

TABLE 11 Prediction accuracy of different parametric and semiparametric models

	Before reform		After reform	
	1-year	2-year	1-year	2-year
Full sample				
Plackett	0.07	0.08	0.08	0.16
Semi-nonpar copula	0.02	0.03	0.03	0.06
Men only				
Plackett	0.13	-	0.23	-
Semi-nonpar copula	0.04	-	0.08	-
Women only				
Plackett	0.15	-	0.28	-
Semi-nonpar copula	0.05	-	0.06	-
25- to 55-year-old men				
	1-year	2-year	1-year	2-year
Plackett	0.22	-	0.33	-
Semi-nonpar copula	0.05	-	0.10	-

in mobility in the bottom earnings decile is associated with both: (i) a decrease in upward mobility of minimum wage workers from the first to the second bottom earnings decile and (ii) a decrease in downward mobility towards minimum wage jobs, that is, from the second to the first bottom earnings decile.

Consistently with the previous insights obtained with actual transition matrices as well as with the fully parametric copula model, our semi-nonparametric estimation shows that there has been an increase in positional persistence in the bottom part of the residual earnings distribution after minimum wage introduction. This is due, as mentioned above, to a decrease in upward mobility of minimum wage workers, as well as to a decrease in downward mobility into minimum wage jobs. In order to adequately compare the performance of the different models, in Table 11, we report a sort of (chi-square) aggregate measure of prediction accuracy. This measure is computed as follows:

$$PredAccuracy_m = \sum_{i=1}^{5}\sum_{j=1}^{5}(P_{ijm} - A_{ij})^2/A_{ij} \tag{12}$$

where ij stands for each cell of a transition matrix (i stands for the row and j for the column) and m represents the model used to produce the predictions, that is, fully parametric Plackett copula or the semi-nonparametric copula. A_{ij} is the actual transition probability observed in cell ij and and P_{ijm} is the transition probability predicted with model m for the same cell ij. From Table 11, we deduce that, both on the 1-year and on the 2-year horizon, the semi-nonparametric copula outperforms the fully parametric one. This holds true both in the pre-reform and in the post-reform sample, and it is also confirmed in all the robustness checks performed on the different subsamples.

In addition, from our semi-nonparametric model, we can easily derive the conditional quantiles, which provide us with further information on the conditional distribution of the present rank. The conditional quantile $Q_{Z,t}(u|Z_{i,t-1}, X_{it}, X_{i,t-1})$ of Z_{it} given $Z_{i,t-1}, X_{it}, X_{i,t-1}$ for percentile $u \in (0,1)$ is given by

$$Q_{Z,t}(u|Z_{i,t-1}, X_{it}, X_{i,t-1}) = G^{-1}\left[\tilde{\Lambda}[\tilde{\rho}(G(Z_{i,t-1}|X_{i,t-1}); X_{it}) + \Phi^{-1}(u); X_{it}]|X_{it}\right]. \tag{13}$$

In particular, for $u = 0.5$, we get the conditional median. However, we are mostly interested in conditional quantiles in terms of wages, not in terms of residual wages; hence, we rely on the following equation. The conditional wage quantile for percentile $u \in (0,1)$ is

$$Q_{r,t}\left(u|Z_{i,t-1}, \eta_i, Age_{i,t}, Age^2_{i,t}\right) = b_t\left[Q_{Z,t}(u|Z_{i,t-1}, Age_{i,t}, Age^2_{i,t}), \eta_i, Age_{i,t}, Age^2_{i,t}\right], \tag{14}$$

where $b_t(Z_{i,t}, \eta_i, X_{i,t}) \equiv \hat{F}_{y,t}(\hat{\alpha}_1 Age_{it} + \hat{\alpha}_2 Age^2_{it} + \hat{\sigma}_t\hat{\eta}_i + \hat{F}^{-1}_{\epsilon,t}(\Phi(\tilde{Z}_{i,t}))$, and we substitute to each element its estimated counterpart (see Equation (6)). In Figure 4, we thus report an alternative measure of mobility, which is based on the quantiles defined in Equation (14). The slope of the conditional quantiles of the present wage rank, which are depicted in Figure 4, provides indeed an alternative measure of wage (rank) immobility. From Figure 4, our previous findings are confirmed: we witness a decrease in mobility at the bottom of the earnings distribution after 2015 for 50-year-old workers with high school diploma (before 2015 the slope of the conditional quantile is almost flat at the bottom of the earnings distribution,

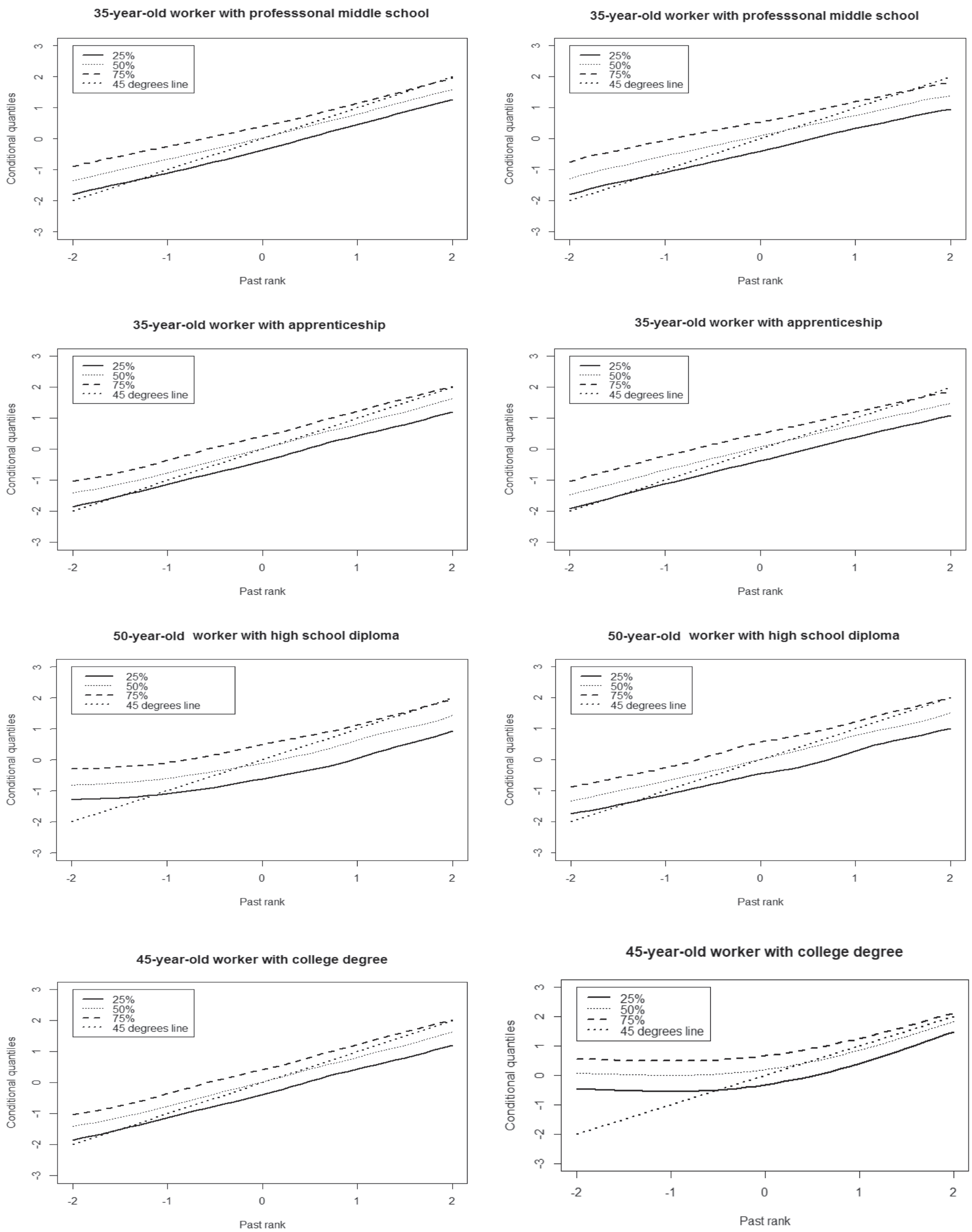

FIGURE 4 Conditional hourly wage quantiles. In this figure, we report three conditional quantiles (median, lower and upper quartiles) as a function of the past Gaussian wage rank for the four sets of individual characteristics, respectively before the the reform (left panels and after the reform (right panels). College here stands for university or professional university. The conditional quantiles are estimated using equation (14) for workers at the first, second, and third quartiles of the present year wage rank distribution ($u = 0.25, 0.50, 0.75$)

this suggests a low degree of association between past and present Gaussian wage ranks). On the other hand, we record an increase in positional mobility at the bottom of the distribution for 45-year-old workers with a college degree. Further, we record essentially no change in the conditional wage quantiles of 35-year-old workers, either with professional middle school or with apprenticeship. Indeed, this type of analysis allows us to assess which groups are mostly affected by permanent changes in mobility patterns.

From Figure 4, we notice that not only our proposed semi-nonparametric model has a better fit to the data than the fully parametric one, but it also allows us to assess that workers with a high school diploma became more persistent at the bottom of the earnings distribution after 2015, whereas the opposite is true for workers with a university or professional university degree. A similar pattern is likely to remain undetected by computing aggregate (unconditional) transition probabilities. Hence, a flexible model is key to uncover individual mobility patterns.

Our main finding of an increase in persistence at the bottom of the earnings distribution is consistent with the hypothesis of firms substituting low-skilled with high-skilled workers after the introduction of a minimum wage. In particular, from Figure 4, we notice that this drop in mobility is driven by experienced workers with high school diploma, who are probably replaced with individuals with a higher educational qualification (e.g., university or professional university degree). This is consistent, for example, with Meer and West (2016). Since individuals with a high school degree represent around 67% of our sample in the first bottom decile (whereas individuals with professional middle school and with apprenticeship account together for around 19% in the first bottom decile), this makes clear that in the aggregate estimation results (i.e., transition matrices), we notice a drop in mobility at the bottom of the wage distribution. Individuals with a university or professional university degree, on the contrary, experienced an increase in their mobility after the reform. This is consistent with the theory of firms substituting low skilled workers with high skilled ones. However, individuals with a university or professional university degree only represent around 14% of workers being in the first bottom decile in our sample.

5 | CONCLUSION

In this paper, we analyzed earnings mobility before and after the introduction of a statutory national minimum wage in Germany on January 1, 2015. We find evidence of an increase in positional persistence at the bottom of the residual earnings distribution after 2015. Such an increase in persistence is associated with both a decline in upward mobility of minimum wage workers and a decline in downward mobility into minimum wage jobs (e.g., from the second to the first bottom earnings decile). These findings are confirmed by both actual transitions recorded in the data and estimation results obtained with a fully parametric and a semi-nonparametric copula. However, the semi-nonparametric model has the advantage of allowing us to estimate the degree of earnings mobility for virtually each individual in our sample. This allows us to uncover that at the root of the increase in persistence at the bottom of the distribution there is a drop in mobility for experienced workers with a high school diploma. Moreover, the semi-nonparametric copula has a better fit to the data as shown in Table 11.

When using the more flexible copula model, we decided not to model zero earnings years, since it would have been computationally not tractable, as explained in Section 1. However, in Section 3, we present some descriptive evidence about the impact of the minimum wage introduction of transitions into and out of unemployment. Empirically, we record a (slight) increase in exit from unemployment (consistently with the search and match model) and essentially no change in entry in unemployment from the first bottom earnings decile. As far as overall unemployment is concerned, we record essentially stable numbers from 2011 through 2018, as reported in Table 2. Finding a way to include the modelling of zero years into the functional copula model represents an avenue for further research.

ACKNOWLEDGMENTS

I would like to thank two anonymous referees, Patrick Gagliardini and Blaise Melly, for their insightful advice.

OPEN RESEARCH BADGES

This article has earned an Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results.

DATA AVAILABILITY STATEMENT

Data is available at http://qed.econ.queensu.ca/jae/datasets/naguid001/.

REFERENCES

Acemoglu, D., & Pischke, J.S. (1999). The structure of wages and investment in general training. *Journal of Political Economy*, *107*(3), 539–572.

Ahlfeldt, G.M., Roth, D., & Seidel, T. (2018). The regional effects of Germany's national minimum wage. *Economics Letters*, *172*, 127–130.

Arellano, M., Blundell, R., & Bonhomme, S. (2017). Earnings and consumption dynamics: A nonlinear panel data framework. *Econometrica*, *85*(3), 693–734.

Askenazy, P. (2003). Minimum wage, exports and growth. *European Economic Review*, *47*(1), 147–164.

Bonhomme, S., & Robin, J.M. (2009). Assessing the equalizing force of mobility using short panels: France, 1990–2000. *The Review of Economic Studies*, *76*(1), 63–92.

Bossler, M., & Gerner, H.D. (2020). Employment effects of the new German minimum wage: Evidence from establishment-level microdata. *ILR Review*, *73*(5), 1070–1094.

Bossler, M., & Schank, T. (2020). Wage inequality in Germany after the minimum wage introduction Working Paper.

Brown, A.J., Merkl, C., & Snower, D.J. (2014). The minimum wage from a two-sided perspective. *Economics Letters*, *124*(3), 389–391.

Cahuc, P., & Michel, P. (1996). Minimum wage unemployment and growth. *European Economic Review*, *40*(7), 1463–1482.

Caliendo, M., Fedorets, A., Preuss, M., Schroder, C., & Wittbrodt, L. (2018). The short-run employment effects of the German minimum wage reform. *Labour Economics*, *53*, 46–62.

Caliendo, M., Wittbrodt, L., & Schröder, C (2019). The causal effects of the minimum wage introduction in Germany—An overview. *German Economic Review*, *20*(3), 257–292.

Cardoso, A.R. (2006). Wage mobility: Do institutions make a difference? *Labour economics*, *13*(3), 387–404.

Clemens, J. (2021). How do firms respond to minimum wage increases? understanding the relevance of non-employment margins. *Journal of Economic Perspectives*, *35*(1), 51–72.

David, H., Manning, A., & Smith, C.L. (2016). The contribution of the minimum wage to US wage inequality over three decades: a reassessment. *American Economic Journal Applied Economics*, *8*(1), 58–99.

Dickens, R. (2000). Caught in a trap? Wage mobility in Great Britain: 1975-1994. *Economica*, *67*, 477–197.

Dube, A., Lester, T.W., & Reich, M. (2016). Minimum wage shocks, employment flows, and labor market frictions. *Journal of Labor Economics*, *34*(3), 663–704.

Dustmann, C., Lindner, A., Schönberg, U., Umkehrer, M., & Vom Berge, P. (2022). Reallocation effects of the minimum wage. *The Quarterly Journal of Economics*, *137*(1), 267–328.

Falk, A., Fehr, E., & Zehnder, C. (2006). Fairness perceptions and reservation wages—The behavioral effects of minimum wage laws. *The Quarterly Journal of Economics*, *121*(4), 1347–1381.

Fernández-Val, I., & Vella, F. (2011). Bias corrections for two-step fixed effects panel data estimators. *Journal of Econometrics*, *163*(2), 144–162.

Fields, G.S., & Ok, E.A. (1999). The measurement of income mobility: An introduction to the literature. Springer Netherlands, 557-598. *Bulletin*, *26*(4), 1–20.

Flinn, C.J. (2006). Minimum wage effects on labor market outcomes under search, matching, and endogenous contact rates. Econometrica, 74(4), 1013-1062. inference. *Journal of Econometrics*, *120*(1), 181–205.

Garloff, A. (2019). Did the German minimum wage reform influence (un) employment growth in 2015? Evidence from regional data. *German Economic Review*, *20*(3), 356–381.

Gernandt, J. (2009). Decreasing wage mobility in Germany. *ZEW-Centre for European Economic Research Discussion Paper*, 9–44.

Giuliano, L. (2013). Minimum wage effects on employment, substitution, and the teenage labor supply: Evidence from personnel data. *Journal of Labor Economics*, *31*(1), 155–194.

Hahn, J., & Kuersteiner, G. (2011). Bias reduction for dynamic nonlinear panel models with fixed effects. *Econometric Theory*, *27*(6), 1152–1191.

Hryshko, D. (2012). Labor income profiles are not heterogeneous: Evidence from income growth rates. *Quantitative Economics*, *3*(2), 177–209.

Hu, Y., Moffitt, R., & Sasaki, Y. (2019). Semiparametric estimation of the canonical permanent-transitory model of earnings dynamics. Quantitative Economics. Forthcoming.

Joe, H. (1997). *Multivariate models and multivariate dependence concepts*. CRC Press.

Lancaster, T. (2000). The incidental parameter problem since 1948. *Journal of econometrics*, *95*(2), 391–413.

Lee, D., & Saez, E. (2012). Optimal minimum wage policy in competitive labor markets. *Journal of Public Economics*, *96*(9), 739–749.

Manning, A. (2021). The elusive employment effect of the minimum wage. *Journal of Economic Perspectives*, *35*(1), 3–26.

Meer, J., & West, J (2016). Effects of the minimum wage on employment dynamics. *Journal of Human Resources*, *51*(2), 500–522.

Naguib, C., & Gagliardini, P. (2020). Wage mobility: A functional copula approach SSRN working paper.

Nelsen, R.B. (1999). *An introduction to copulas*. Vol. *139*, Springer Science and Business Media.

Neumark, D., Schweitzer, M., & Wascher, W. (2004). Minimum wage effects throughout the wage distribution. *Journal of Human Resources*, *39*(2), 425–450.

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

Nickell, S., & Layard, R. (1997). *The labour market consequences of technical and structural change*, Discussion Paper Series: Oxford University. 23.

Pavlopoulos, D., Fouarge, D., Muffels, R., & Vermunt, J. (2007). Job mobility and wage mobility of high-and low-paid workers. *Schmollers Jahrbuch*, *127*(1).

Plackett, R.L. (1965). A class of bivariate distributions. *Journal of the American Statistical Association*, *60*(310), 516–522.

Romer, P.M. (1986). Increasing returns and long-run growth. *Journal of political economy*, *94*(5), 1002–1037.

Romer, P.M. (1989). Human capital and growth: Theory and evidence NBER working paper.

Shorrocks, A.F. (1978). The measurement of mobility. *Econometrica: Journal of the Econometric Society*, 1013–1024.

Stewart, M.B (2012). Wage inequality, minimum wage effects, and spillovers. *Oxford Economic Papers*, *64*(4), 616–634.

Wooldridge, J.M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics*, *20*(1), 39–54.

Zavodny, M. (2000). The effect of the minimum wage on employment and hours. *Labour Economics*, *7*(6), 729–750.

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How to cite this article: Naguib C. Did earnings mobility change after minimum wage introduction? Evidence from parametric and semi-nonparametric methods in Germany. *Journal of Applied Econometrics*. 2022;1–24. https://doi.org/10.1002/jae.2926