Empirical analysis of social insurance, work incentives and employment outcomes

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2 A panel data sample selection model to estimate life-cycle earning profiles: How important is selection into full-time and part-time employment?

Abstract

This paper proposes a new panel data sample selection model with 1) ordered discrete choices in the selection equation and 2) non-parametric unobserved heterogeneity in the equation of interest. This method is used to estimate life-cycle earnings profiles using high-quality administrative data. We compare conclusions regarding the existence and direction of selection into (part-time) work among men and women across different panel data sample selection techniques. The main conclusion is that our new approach is able to control for important unobserved heterogeneity from intensive labor supply choices with important consequences for the existence and direction of selection in (part-time) work.

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2.1 Introduction

Estimating earnings profiles is crucial for understanding earnings dynamics and life-cycle consumption and savings decisions. Since earnings are only observed among those who work, simply estimating an earnings model without taking into account the non-random selection into work leads to serious inconsistent estimates of earnings (Heckman 1979), even in the case of panel data (Solon 1988). In light of this selection issue, many of the earnings processes estimated in the literature focus on prime age males as it can be argued that this group is most likely to work (full time) and least likely to self-select into work.[1] This also holds for recent estimates of life-cycle wages (Lagakos et al. 2018), which are estimated solely on full-time public sector male workers. As a consequence, conclusions from such estimates may not be generalizable to women[2] and older men[3] for whom working (full time) is less self-evident. Hence, it is important to derive models that correct for sample selection with panel data and test the assumption of no selection into (full-time) work among both men and women to get an impression of the generalizability of results for prime age males. In this paper, we test if there is additional information hidden in selection into part-time versus full-time employment compared to selection in employment at the extensive margin to estimate selection-corrected earnings profiles.

The first panel data sample selection models are derived by Wooldridge (1995), Kyriazidou (1997), and Rochina-Barrachina (1999) who build upon the sample selection model of Heckman (1979).[4] The three methods differ in the assumptions and estimation of the first-stage and second-

[1]See, for example, Baker (1997), Baker and Solon (2003), Daly et al. (2022), Gottschalk and Moffitt (1994), Guvenen (2009), Heathcote et al. (2010), Lillard and Weiss (1979), Lillard and Willis (1978), Meghir and Pistaferri (2004, 2010), Moffitt and Gottschalk (2012), Pischke (1995), Storesletten et al. (2004).

[2]Ermisch and Wright (1993), for example, find positive selection of women into full-time work in the UK.

[3]Myck (2010), for example, shows that lower paid older men are more likely to remain in employment than higher paid older men in the UK, i.e. negative selection. This is consistent with evidence from Hanoch and Honig (1985) for American men and women.

[4]A newer strand of literature extends these models in the direction of making fewer parametric assumption (Semykina and Wooldridge 2018), allowing for endogenous regressors (Charlier et al. 2001, Dustmann and Rochina-Barrachina 2007, Semykina and Wooldridge 2010), and dynamic models (Semykina and Wooldridge 2013).

stage of the model.[5] Both Wooldridge (1995) and Rochina-Barrachina (1999) propose parametric estimators of the linear panel data model under sample selection when the explanatory variables are strictly exogenous. Kyriazidou (1997) derives a semi-parametric estimator for such models. Wooldridge (1995) proposes estimation in levels and makes parametric assumptions on the unobserved individual-specific heterogeneity in both the first- and second-stage. Rochina-Barrachina (1999) proposes estimation in first-differences and makes no parametric assumptions on the unobserved individual-specific heterogeneity in the second-stage and exploits the autoregressive nature of participation to condition on unobserved individual-specific heterogeneity.

All aforementioned estimators assume that selection into earnings is a matter of selecting into work versus non-work (i.e. extensive labor supply decisions) and, therefore, use a binary selection rule. A different strand of literature has not extended the model of Heckman (1979) in the direction of panel data, but by using non-binary choices in the selection equation. Extending selection into work beyond a binary selection rule and allowing for labor supply decisions at the intensive margin may add important unobserved information to the wage equation, such as leisure-time preferences. Only few papers, like Zabalza et al. (1980), Nakamura and Nakamura (1983), Hotchkiss (1991), and Ermisch and Wright (1993), have argued to use an ordered selection rule[6] to capture self-selection into full-time and part-time work. Unlike the first-mentioned strand of literature, these models are only applicable to cross-sectional data and not to panel data.

To be able to distinct between age- and cohort effects in the estimation, it is important to use a panel data sample selection model to estimate the earnings over the life-cycle. The first attempt to combine panel data with adjustments for self-selection into work, and thereby extend the canonical sample selection model of Heckman (1979) to panel data, is by Hanoch and Honig (1985) although their model only uses cohort- and period fixed

[5]Dustmann and Rochina-Barrachina (2007) show how these different assumptions affect the application to real world panel data.

[6]Using an ordered selection rule is consistent with Averett and Hotchkiss (1997), Tummers and Woittiez (1991), Van Soest (1995) who argue that labor supply is semi-continuous.

effects and no individual fixed effects. The first paper to bridge the gap between the two extensions of the Heckman (1979) sample selection model is Dustmann and Schmidt (2000). Dustmann and Schmidt (2000) is the first to use an ordered selection rule in a panel data sample selection model by extending the approach in Wooldridge (1995) from a binary to an ordered selection rule. Like Wooldridge (1995), both the first- and second stage make parametric assumptions about the unobserved effects (Dustmann and Schmidt 2000).

In this paper, we propose a new panel data sample selection model with an ordered selection rule. Compared to Dustmann and Schmidt (2000), we make no parametric assumptions on the unobserved individual-specific heterogeneity in the wage equation and allow to condition on the unobserved individual-specific heterogeneity in participation by exploiting the autoregressive nature of labor supply decisions like Rochina-Barrachina (1999). Compared to Rochina-Barrachina (1999), we use an ordered instead of binary selection rule.

Using administrative panel data that are representative for the Netherlands in the period 2001-2014, we show how an ordered selection rule in the framework of Rochina-Barrachina (1999) can provide additional information for the estimation of earnings over the life-cycle compared to a binary estimator. This may especially hold for the Netherlands where the prevalence of part-time work is internationally high among both men (2020: 28.5%) and women (2020: 73.8%) (OECD 2020). Furthermore, rich administrative data allows us to use very flexible functional forms, such as semi-parametric age effects like in Kalwij and Alessie (2007).

The empirical application of our panel data sample selection model to estimating life-cycle earnings shows that it is important to take self-selection in the intensive margin of labor supply into account. When correcting for the labor supply decision on the intensive margin, we find positive selection into part-time work for both men and women. This means that men and women with more affluent characteristics self-select into part-time employment. Not correcting for such selection leads to an overestimation of part-time earnings. For full-time work, we find positive selection for women only. For full-time men, we find no statistical evidence for selection. Hence, the generally assumed absence of selection into work among men in the literature is only true if full-time work is considered. Our findings regarding the existence and direction of selection are in stark contrast with conclusions based on applying the Rochina-Barrachina (1999) method – with a binary selection rule, which show negative selection into part-time work for men (and none for women) and full-time work for both men and women. Hence, our new approach exploits important unobserved information that stays hidden otherwise and which has implications for understanding who selects into (part-time) work.

Applying our method to estimate life-cycle earnings profiles, we show that correcting for selection changes the earnings estimates significantly and results in different shapes of the earnings-age curve over the life-cycle compared to regular first-differences estimates. With our proposed method, we find that earnings in full-time employment peak later in the life-cycle than earnings in part-time employment. This is true for both men and women. Additionally, these differences are amplified when correcting for selection into full-time and part-time employment.

The remainder of the paper is organized as follows. In the next section, we show the importance of part-time employment in the Netherlands by describing the institutional setting. In section 2.3 contains a description of the data and shows the employment, earnings and wages over the life-cycle. section 2.4 describes the new model and explains the empirical specification. section 2.5 reports the main estimation results. In section 2.6, we investigate the importance of an ordered selection rule compared to a binary rule (the estimator proposed by Rochina-Barrachina 1999). Finally, section 2.7 concludes.

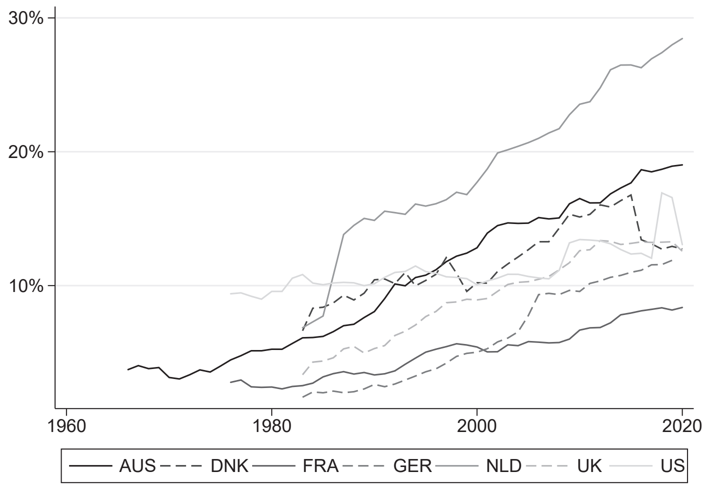
2.2 Institutional background: Part-time employment in the Netherlands

In Figure 2.1, we show the development of part-time employment for a selection of OECD countries for men and women, respectively. From the figures, four general conclusions stand out. First, the incidence of part-time employment is substantial in OECD countries and has been steadily increasing since the late 1960s. Second, part-time employment has in all countries a higher incidence among women than among men. In 2020, the OECD average of part-time employment as a percentage of total employment was 12.4% for men and 31.3% for women. Third, much of the increase in part-time employment across countries is largely due to increasing part-time employment among men (who have higher overall employment rates). Between 1966 and 2020, the incidence of male and female part-time employment grew with 235% (from 3.7% to 12.4%) and 30% (from 24.0% to 31.2%), respectively. Fourth, part-time employment is much more prevalent in the Netherlands than in any of the other (reported and non-reported) OECD countries. This applies to both men (28.5% in 2020) and women (73.8%). These statistics show the relevance of analyzing the selection effects in the intensive margin as the popularity of part-time employment has widely increased and is no longer specific to women only.

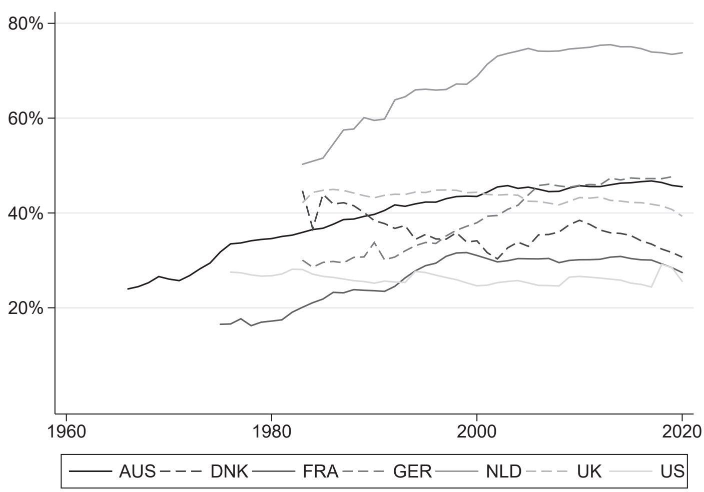
Unlike other countries, most of the part-time employment is on a voluntary basis in the Netherlands (Visser et al. 2004). In the Netherlands, employers are in principle obliged to accept a request for part-time employment of an employee. According the labor law (*Wet Aanpassing Arbeidsduur, WAA*), employees are allowed to request for a decrease (or increase) in their contractual employment hours without any further specification as to the reason why. This only applies to employers with more than 10 employees, employees working at the employer for at least one year, and has a two-month notice. Such a request can be made once a year. The *WAA* implies that part-time employment is highly institutionalized in the Netherlands. Prior to the *WAA*, which was introduced in February 2000, many collective bargaining agreements included the possibility for part-time employment requests. Since January 2016, the flexibility of choosing the number of hours has been extended to flexibility in the daily work hours and location by a law stimulating flexible work (*Wet Flexibel Werken, WFW*). To summarize, these labor laws indicate that flexible work, including part-time work is highly facilitated and accepted in the Netherlands. Additionally, part-time work of couples is facilitated through the tax system, including child care subsidies.

Figure 2.1: Incidence of part-time employment among (a) men and (b) women in OECD countries.

(a) Men (OECD 2020).



(b) Women (OECD 2020).



2.3 Data

2.3.1 Data selection and variable definitions

We use two data sets for our analysis: (i) administrative tax records from the Dutch Income Panel Study from the Netherlands (IPO) for the years 2001-2014, and (ii) data on working hours from the Dutch payroll administration for the years 2001-2014. The IPO data set consists of an administrative panel data set for a representative sample from the Dutch population of, on average, 95,000 selected individuals per year who are followed longitudinally.[7] The data set contains detailed information on personal and household income, labor market status and demographics.

The main advantages of using these administrative data sets compared to using survey data for our analysis are the large sample size, the long panel aspect of the data, the accuracy of tax data compared to self-reported survey answers, and representativeness. Interestingly, the data include a "part-time employment factor", that measures the proportion of work a person has undertaken in relation to a full-time job over the course of a year. A factor of 1 indicates that a person worked full time for the entire year. However, a factor of 0.5 can have two different interpretations: (i) the person worked half of a full-time contract throughout the entire year, or (ii) the person worked full-time for half of the year. We are particularly interested in (i) and not in (ii). Appendix 2.C.2 describes year-to-year transitions in labor supply categories and shows that most individuals stay in the same category from year to year. The dependent variable in our analysis is the full-time equivalent (before tax) wage expressed in (log) 2015 euros. To construct the full-time equivalent wages, we divide yearly earnings by the part-time employment factor mentioned above. Inevitably, we do not observe wages for people who are not wage employed.[8]

[7]Sampling is based on individuals' national security number, and the selected individuals are followed together with their household members for as long as they are residing in the Netherlands on December 31 of the sample year. Individuals born in the Netherlands enter the panel for the first time in the year of their birth, and immigrants to the Netherlands in the year of their arrival.

[8]This includes the self-employed. Following Bardasi and Gornick (2008) we categorize all persons in non-paid employment as 'unemployed.'

In this study we select individuals between the ages of 24 and 64 (387,841 observations for men and 385,298 observations for women). To reduce measurement error, we restrict the sample in the following ways. First, per year, we regard observations below the minimum wage and in the top 1% of the wage distribution as outliers and exclude these from the analysis. Second, per year, observations with the 1% largest decreases or increases in relative year-to-year-changes in the full-time equivalent wage rate are considered outliers and removed. It is likely that such substantial changes in year-to-year wages are a consequence of measurement error in the part-time employment factor (due to the definition of this measure defined by Statistics Netherlands, as explained above). Third, since people who leave employment as a result of a disability might result in measurement error of the part-time employment factor, we drop observations of workers who received disability benefits during (part of) the year. Fourth, we exclude individuals who worked less than one-twelfth of a full-time year. We argue they worked too little to calculate a reliable (full-time equivalent) wage. Fifth, we restrain the sample to individuals who remain in the same labor supply category.[9] This reduces our sample to 266,950 males and 265,305 females. Finally, we use population weights to account for representativity with respect to age, gender, marital status, province, household size and the age of the head of the household.

Descriptive statistics 2.3.2

Earnings

Figure 2.2 presents average earnings profiles for men and women (including those who do not work), with eminent differences between them. The earnings profile of men depicts the typical inverted U-shape moderately well as the wages grow over the life-cycle and only declines sharply in the years in which people retire. For men, average earnings are about 25,000

[9]Appendix 2.C.2 shows that most people remain in the same labor participation category. A change is often caused by individuals becoming unemployed or starting a job during the calendar year and in this case we can not determine for all years the actual labor supply category during the part of the year that people are at work.

euros per year at the age of 25 and grow up to just over 40,000 euros per year around the age of 50. After the age of 50 we observe a decline in average yearly earnings, with the largest drop in earnings around the age of 60. The decline in average earnings among older men may be explained by several phenomena: (i) early retirement, (ii) drops in hours worked preceding retirement (partial retirement), (iii) older workers receiving lower wages and (iv) birth-cohort effects. Negative selection into work at older ages might strengthen this decline (Casanova 2010, Myck 2010).

For women, we see that the earnings are declining after the age of 30. We observe that a 25 year-old female earns about 22,000 euros per year on average. Around the age of 35 (when most women raise their children) earnings are relatively low, probably because of a drop in the labor force participation and/or the number of hours work. Thereafter, earnings remain fairly stable and as from the age of 50 earnings decrease again. However, we should keep in mind that there are profound cohort effects among women. These cohort effects – namely the increased labor force participation and higher educational attainment among younger generations of women – can likely explain the substantial vertical differences between the cohorts among women (which we do not see for men).

Participation

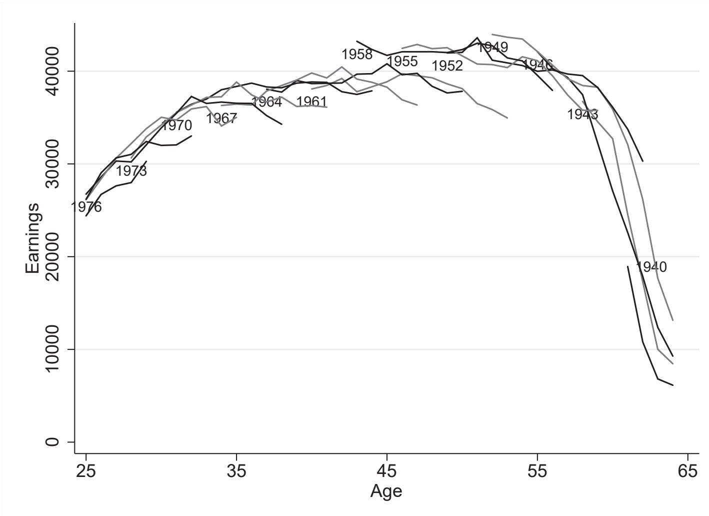
Unemployment and part-time employment shape the earnings profiles as shown in figure 2.2.[10] Figure 2.3 therefore shows the percentage in full-time and part-time employment over the life-cycle for different cohorts for men and women separately. In 2001 about 70% of all men in all cohorts seem to work full-time until the age of 55.[11] However, between 2001 and 2014 it seems at all ages about 10% of the men moved from a full-time to a part-time job. Most men seem to leave the labor market at older ages. About 20% is unemployed at the age of 55 and this increases to about 80% at the age of 64. These changes in employment are almost entirely

[10]Recall that in this paper we define people to be unemployed when they do not earn labor income from paid employment.

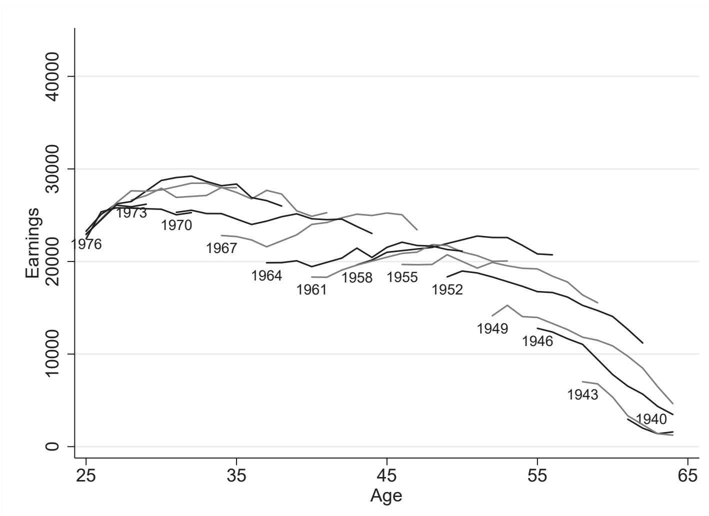
[11]We assume persons to be working full-time if the part-time employment factor is equal to one. Every person with a part-time employment factor of smaller than one is considered to be working part-time or unemployed.

Figure 2.2: Life-cycle earnings of men (a) and women (b)

(a) Mean earnings men



(b) Mean earnings women



confined to transitions from full-time employment into unemployment. As expected, younger cohorts of men retire later.

The employment patterns for women are different than those for men, with lower employment rates and more part-time work, especially among older women. This is also depicted in Table 2.2, where we show how participation has evolved over time. Whereas participation of men is fairly stable or even declined over time, we observe a substantial increase in women's participation (10%-points in 15 years). Although the literature generally suggests that women's labor supply is largely affected by changes in child care subsidies, see among others (Berger and Black 1992), such effects are found to be small in the Netherlands (Bettendorf et al. 2015).

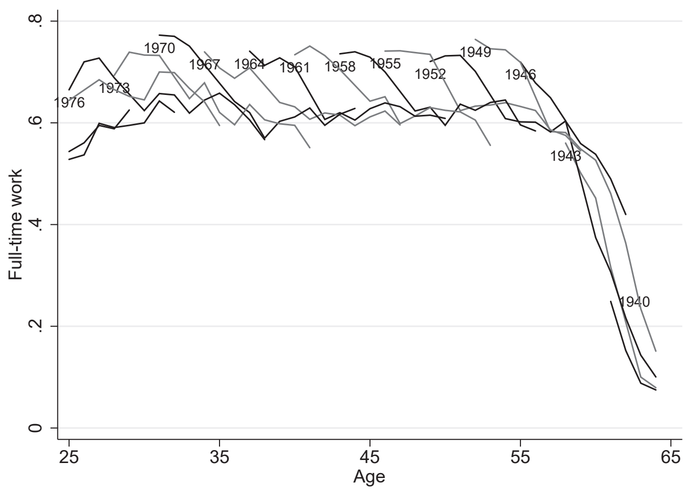
For women, we observe a substantial drop in full-time employment around the age at which they raise children. Before the age of 30 about 40-50% of women work full-time and this drops to about 20% at the age of 40, after which it stays constant until the age of 55. This is in line with the findings of Bosch et al. (2010). Part-time work, on the other hand, increases between the age of 30 and 40 from about 40 to 55%. The large shift from full-time employment to part-time or unemployment also largely explains the earnings decline as depicted in panel (b) of Figure 2.2. Similarly to men, women leave the labor market at older ages. Finally, employment is much higher for younger cohorts than for older cohorts of women.

Wages

Figure 2.4 shows the average yearly wage (on a full-time basis) for men and women in full-time and part-time employment. Although we found an inverted U-shape for life-cycle earnings of men, wages are increasing over the life-cycle. Average yearly wages are approximately 33,000 euros at the age of 25 for men in full-time employment, and about 30,000 euros in part-time employment. Both full-time and part-time wages increase with age, with the largest changes in the beginning of the career. Full-time wages are on average 53,000 euros before retirement, while part-time wages end around 50,000 euros.

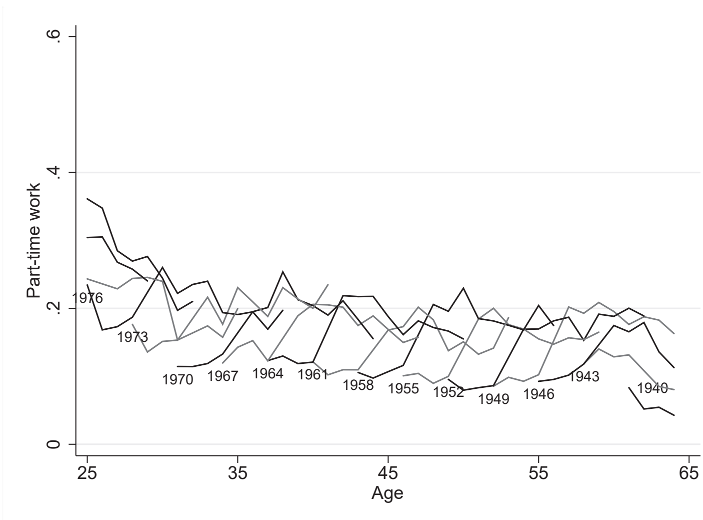
Figure 2.3: Percentage of men and women in full-time and part-time employment

(a) Full-time employment (%) of men



(b) Full-time employment (%) of women

(c) Part-time employment (%) of men



(d) Part-time employment (%) of women

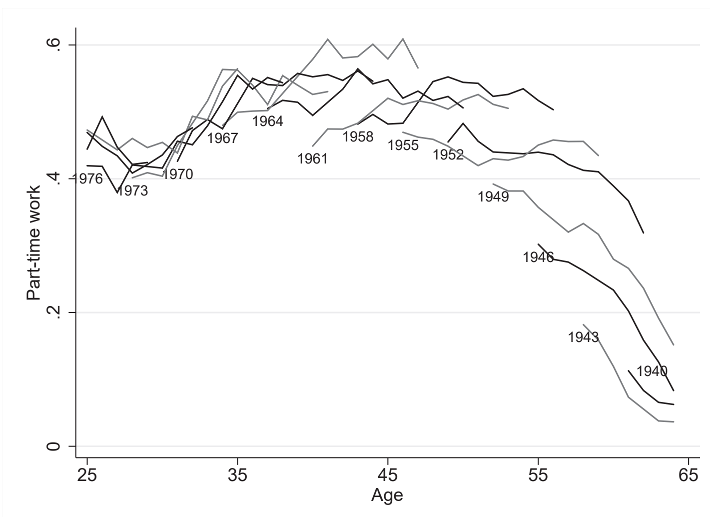
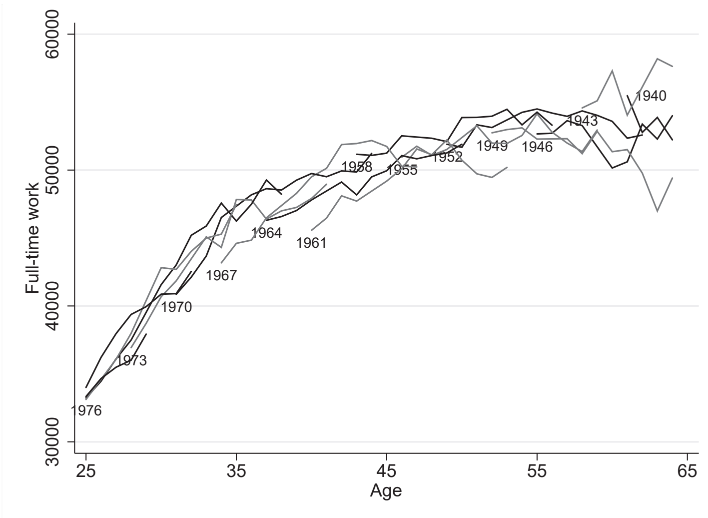
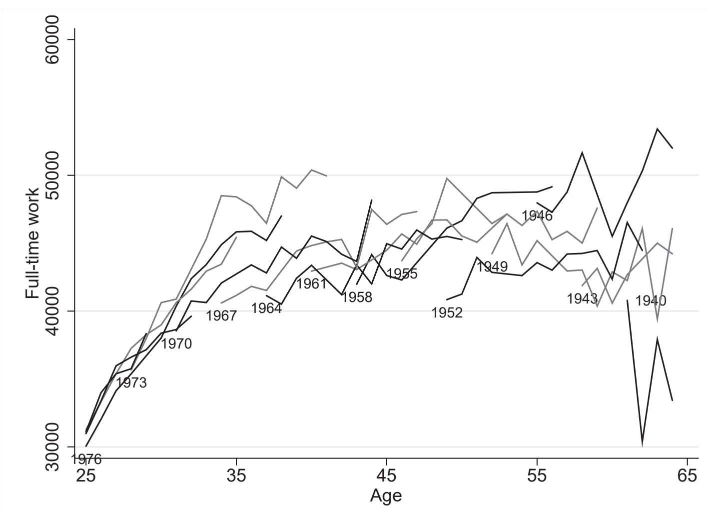


Figure 2.4: Wage of men and women in full-time and part-time employment

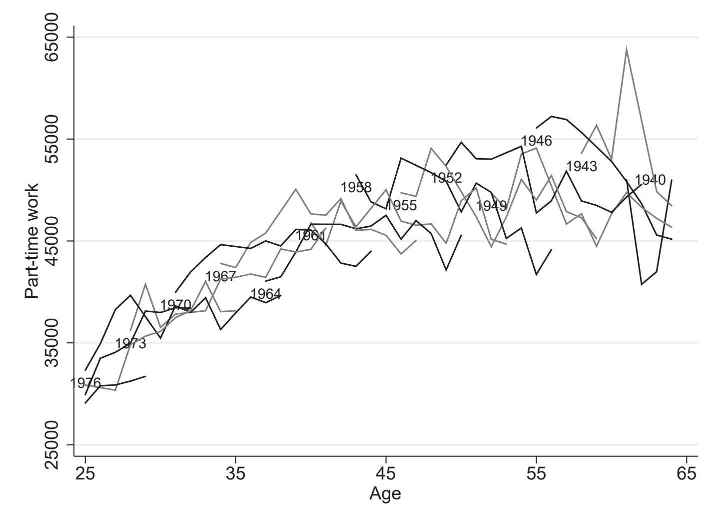
(a) Full-time wages of men



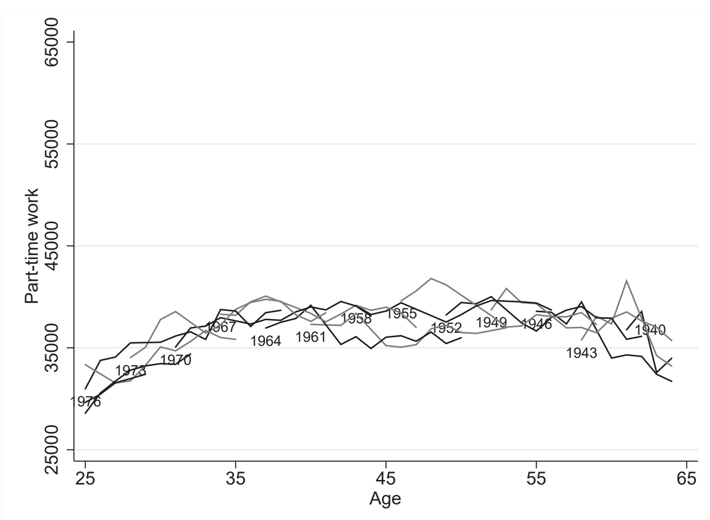
(b) Full-time wages of women



(c) Part-time wages of men



(d) Part-time wages of women



Female yearly average wages also show large increases over the life-cycle. Although part-time and full-time wages both increase with age, full-time wages show a larger and more persistent growth. This results in an increase from around 30,000 euros at the age of 25 (for both full-time and part-time work) to 45,000 euros at the age of 45 for women in full-time employment, and less than 40,000 euros for those in part-time employment. Thereafter wages remain relatively constant. Appendix 2.A also shows the trends in (part-time) participation and wages over the time period 2001-2014 for both men and women.[12]

Model 2.4

The previous section showed that full-time wages are higher than the full-time equivalent of part-time wages and that wages grow over the life-cycle. However, to be able to correctly estimate the life-cycle earnings profiles, we should take into account that we only observe wages for those individuals who are working and that workers might select into (part-time) employment. As a result, these workers might differ in both observed as well as unobserved characteristics. Accordingly, the goal of the remainder of the paper is to estimate life-cycle wage profiles for men and women in both full-time and part-time employment while controlling for selection on observed and unobserved heterogeneity. To do so, we first introduce our panel data sample selection model with an ordered selection rule and no parametric assumptions on the individual-specific heterogeneity in the wage equation.

[12]We observe a discontinuity in the hours worked around 2006, which especially affects our part-time employment variable. This discontinuity is also addressed by De Nardi et al. (2021), who show similar patterns in (part-time) employment for the 2001-2014 and the post-2006 periods. We test the robustness of our results using a dummy for the post-2006 period in the wage equation. The dummy is significant, however, with a coefficient of 0.016 the effect is not substantial. Our main conclusions remain the same when adding this dummy.

2.4.1 Panel data sample selection model

Suppose that we have two individuals A and B with the same observed characteristics. A is working part-time and B is working full-time. B most likely has more favorable unobserved characteristics (like ability and motivation) which lead both to more hours worked and a higher wage rate. As long as these unobserved characteristics are time-invariant we can use a individual fixed-effects data model to take this into account. However, it is likely that there are also time variant unobserved characteristics such as time variant unobserved ability or health that influence both participation, the number of hours worked, and the wage rate of individual i in period t. To take this into account we use a panel data sample selection model that models both wages and labor force participation at the extensive and intensive margin. The model can be written as follows:

$$y_{it}^* = x_{it}\beta + \alpha_i + u_{it} \quad i = 1, ..., N \quad t = 1, ..., T \tag{2.1}$$

$$h_{it}^* = z_{it}\gamma_t + \eta_i + v_{it} \tag{2.2}$$

$$y_{it} = \begin{cases} y_{it}^* & \text{if } h_{it}^* > \delta_{1t} \\ \text{unobserved} & \text{otherwise} \end{cases} \tag{2.3}$$

$$h_{it} = \begin{cases} 0 \quad \text{(no participation)} & \text{if } h_{it}^* \leq \delta_{1t} \\ 1 \quad \text{(part-time)} & \text{if } \delta_{1t} < h_{it}^* \leq \delta_{2t} \\ 2 \quad \text{(part-time)} & \text{if } \delta_{2t} < h_{it}^* \leq \delta_{3t} \\ \vdots & \\ J \quad \text{(full-time)} & \text{if } \delta_{Jt} < h_{it}^* \end{cases} \tag{2.4}$$

where y_{it} is the observed wage for individual i in period t. h_{it} is the observed labor force participation containing J categories of labor (no labor force participation, several categories of part-time labor force participation, and full-time labor force participation). h_{it}^* indicates the latent equivalent. x_{it} and z_{it} are vectors of individual's observed characteristics. For identification, z_{it} includes variables that do not appear in x_{it}. β and γ_t are unknown parameter vectors to be estimated and α_i and η_i are unobserved individual-specific effects, which are possibly correlated with x_{it} and z_{it}.

They capture education, time-invariant ability, and cohort effects that incorporate participation and productivity differences between generations (Kapteyn et al. 2005). δ_{jt} with $j = \{1, .., J\}$ are time-specific thresholds to be estimated. Finally, u_{it} and v_{it} are unobserved disturbances which are assumed to follow a normal distribution with mean zero and variances $\sigma_{u,t}$ and $\sigma_{v,t}$.

Presumably, u_{it} and v_{it} are correlated and therefore we need to incorporate selection into the wage equation. Furthermore, because u_{it} is likely to be serially correlated, we use the first difference (FD) estimator in the main equation.[13] FD requires a weaker form of exogeneity than what is required for FE. Namely $E(x_{it}u_{is}) = 0$ for $s = t, t-1$ instead of $E(x_{it}u_{is}) = 0$ for $s = 1, 2, ...T$. Thus, FD allows that past wage shocks affect the explanatory variables later in life ('feedback effects'), which may be necessary as the selection correction terms (which we explain below) may not be strictly exogenous in the main equation.

We use a discrete choice model to model the allocation to part-time and full-time jobs. Discrete choice models have been used repeatedly in the literature to model the allocation to part-time and full-time jobs.[14] In this way we account for mass points in the number of hours worked (e.g. because of work hour restrictions) like Van Soest (1995). A drawback is the incomplete use of available data, however, the number of labor supply categories J can be increased to allow for more differentiation in labor supply, but increasing J goes at the cost of statistical power per category. The optimal number of categories J is found to be arbitrary (Franses and Cramer 2010).

We can only observe wage differences for those observations for which an individual has worked at both time t and $t-1$:

$$y_{it} - y_{it-1} = \begin{cases} y^*_{it} - y^*_{it-1} & \text{if } h^*_{it-1} > \delta_{1,t-1} \text{ and } h^*_{it} > \delta_{1,t} \\ \text{unobserved} & \text{otherwise} \end{cases} \tag{2.5}$$

[13]We find evidence of serial correlation in wages in our data. The Wooldridge (2002) test for autocorrelation in panel data rejects the null-hypothesis of no first-order autocorrelation for men (*F-stat=7.22*, p-value=0.0072) and women (*F-stat=56.46*, p-value=0.0000).

[14]See, for example, Duncan and Weeks 1997, Dustmann and Schmidt 2000, Ermisch and Wright 1993, Hotchkiss 1991, Nakamura and Nakamura 1983, Zabalza et al. 1980.

where

$$y^*_{it} - y^*_{it-1} = (x_{it} - x_{it-1})\beta + (u_{it} - u_{it-1}) \tag{2.6}$$

Since the first-difference in wages ($y_{it} - y_{it-1}$) is only observed if a person actually worked in both periods ($h^*_{it-1} > \delta_{1,t-1}$ and $h^*_{it} > \delta_{1,t}$), estimating Equation (2.6) by OLS would yield inconsistent estimates of β as the conditional expectation of the error term is unlikely to be zero due to correlation between u_{it} and v_{it}. Therefore, we need to calculate the expectation conditional on participation. We do not only know whether someone is participating, but also whether someone is participating full-time ($h^*_{it} > \delta_{Jt}$) or whether someone is in some part-time labor supply category ($\delta_{jt} < h^*_{it} \leq \delta_{j+1,t}$ where $j = 1, 2, ...J - 1$). This gives us additional information about the unobserved characteristics. The conditional expectation of the first differences can be written as follows:

$$\begin{aligned} &E[y_{it} - y_{it-1} | \, x_{it}, x_{it-1}, z_{it}, z_{it-1}, \delta_{j,t} < h^*_{it} \leq \delta_{j+1,t}, \delta_{j,t-1} < h^*_{it-1} \leq \delta_{j+1,t-1}] \\ &= (x_{it} - x_{it-1})\beta \\ &+ E[u_{it} - u_{it-1} | \, x_i, z_i, \delta_{j,t} < h^*_{it} \leq \delta_{j+1,t}, \delta_{j,t-1} < h^*_{it-1} \leq \delta_{j+1,t-1}] \end{aligned} \tag{2.7}$$

where j is the working hours category of individual i at time t. For persons who do not work at time t, we define $\delta_{0,t} = -\infty$. Similarly, for persons engaged in full-time work at time t, $\delta_{J+1,t} = \infty$.

Following Mundlak (1978) we parameterize the individual specific effect in the selection equation (2.2) as a linear function of the average explanatory variables over time plus a random individual specific effect that is assumed to be independent of the explanatory variables:

$$\eta_i = \overline{z_i}\theta + c_i \tag{2.8}$$

where θ is an unknown parameter vector to be estimated and c_i is assumed to be a normally distributed random variable with mean zero and variance σ_c. Substituting (2.8) into (2.2) yields:

$$h^*_{it} = z_{it}\gamma_t + \overline{z_i}\theta + \mu_{it} \tag{2.9}$$

where $\mu_{it} = c_i + v_{it}$. Given the distributional assumptions it holds that $\mu_{it} \sim N(0, \sigma_{\mu,t})$, where $\sigma^2_{\mu,t} = \sigma^2_c + \sigma^2_{v,t}$. Furthermore, μ_{it} is allowed to be serially dependent (this is necessary, because of the term c_i). Denote the correlation coefficient of μ_{it-1} and μ_{it} by ρ_t. Substituting (2.9) into the last term of (2.7) gives us

$$\begin{aligned}&\mathrm{E}[u_{it} - u_{it-1} | x_i, z_i, \delta_{j,t} < h^*_{it} \leq \delta_{j+1,t}, \delta_{j,t-1} < h^*_{it-1} \leq \delta_{j+1,t-1}] \\ &= \mathrm{E}[u_{it} - u_{it-1} | x_{it}, x_{it-1}, z_{it}, z_{it-1}, a_{it-1} \leq \frac{\mu_{it-1}}{\sigma_{\mu,t-1}} < b_{it-1}, a_{it} \leq \frac{\mu_{it}}{\sigma_{\mu,t}} < b_{it}]\end{aligned} \tag{2.10}$$

where

$$a_{it-1} = (-\delta_{j+1,t-1} + z_{it-1}\gamma_t + \overline{z_i}\theta)/\sigma_{\mu,t-1} \tag{2.11}$$
$$b_{it-1} = (-\delta_{j,t-1} + z_{it-1}\gamma_t + \overline{z_i}\theta)/\sigma_{\mu,t-1} \tag{2.12}$$
$$a_{it} = (-\delta_{j+1,t} + z_{it}\gamma_t + \overline{z_i}\theta)/\sigma_{\mu,t} \tag{2.13}$$
$$b_{it} = (-\delta_{j,t} + z_{it}\gamma_t + \overline{z_i}\theta)/\sigma_{\mu,t} \tag{2.14}$$

The errors $[(u_{it} - u_{it-1}), \mu_{it-1}, \mu_{it}]$ are assumed to be trivariate normally distributed conditional on x_{it-1}, x_{it}, z_{it-1} and z_{it}.

Following the method of the two-step approach proposed by Heckman (1976, 1979), we work out (2.10) to obtain correction terms, that can be added as additional regressors to the main equation (the wage equation). Rochina-Barrachina (1999) also extends Heckman's sample selection technique to the case where one correlated selection rule in two different time periods generates the sample. We extend this further by allowing for an ordered selection indicator.

In order to work out (2.10), we take the derivative of the moment generating function of the doubly truncated trivariate normal distribution with respect to $t-1$ and evaluate this function in $t = 0$. For details regarding the derivation, we refer to Appendix 2.B. The derivation gives us

$$\mathrm{E}(u_{it} - u_{it-1} | x_{it}, x_{it-1}, z_{it}, z_{it-1}, a_{it-1} \leq \frac{\mu_{it-1}}{\sigma_{\mu,t-1}} < b_{it-1}, a_{it} \leq \frac{\mu_{it}}{\sigma_{\mu,t}} < b_{it}) = \tag{2.15}$$

$$\pi_1\lambda_{1it}(\rho_t, a_{it-1}, a_{it}, b_{it-1}, b_{it}) + \pi_2\lambda_{2it}(\rho_t, a_{it-1}, a_{it}, b_{it-1}, b_{it})$$
$$+ \pi_3\lambda_{3it}(\rho_t, a_{it-1}, a_{it}, b_{it-1}, b_{it}) + \pi_4\lambda_{4it}(\rho_t, a_{it-1}, a_{it}, b_{it-1}, b_{it})$$

where

$$\lambda_{1it}(\rho_t, a_{it-1}, a_{it}, b_{it-1}, b_{it}) = \frac{\phi(b_{it-1})\left[\Phi\left((b_{it} - \rho_t b_{it-1})/\sqrt{1-\rho_t^2}\right) - \Phi\left((a_{it} - \rho_t b_{it-1})/\sqrt{1-\rho_t^2}\right)\right]}{\Phi^2(b_{it-1}, b_{it}; \rho_t) - \Phi^2(a_{it-1}, a_{it}; \rho_t)} \tag{2.16}$$

$$\lambda_{2it}(\rho_t, a_{it-1}, a_{it}, b_{it-1}, b_{it}) = \frac{\phi(a_{it-1})\left[\Phi\left((b_{it} - \rho_t a_{it-1})/\sqrt{1-\rho_t^2}\right) - \Phi\left((a_{it} - \rho_t a_{it-1})/\sqrt{1-\rho_t^2}\right)\right]}{\Phi^2(b_{it-1}, b_{it}; \rho_t) - \Phi^2(a_{it-1}, a_{it}; \rho_t)} \tag{2.17}$$

$$\lambda_{3it}(\rho_t, a_{it-1}, a_{it}, b_{it-1}, b_{it}) = \frac{\phi(b_{it})\left[\Phi\left((b_{it-1} - \rho_t b_{it})/\sqrt{1-\rho_t^2}\right) - \Phi\left((a_{it-1} - \rho_t b_{it})/\sqrt{1-\rho_t^2}\right)\right]}{\Phi^2(b_{it-1}, b_{it}; \rho_t) - \Phi^2(a_{it-1}, a_{it}; \rho_t)} \tag{2.18}$$

$$\lambda_{4it}(\rho_t, a_{it-1}, a_{it}, b_{it-1}, b_{it}) = \frac{\phi(a_{it})\left[\Phi\left((b_{it-1} - \rho_t a_{it})/\sqrt{1-\rho_t^2}\right) - \Phi\left((a_{it-1} - \rho_t a_{it})/\sqrt{1-\rho_t^2}\right)\right]}{\Phi^2(b_{it-1}, b_{it}; \rho_t) - \Phi^2(a_{it-1}, a_{it}; \rho_t)} \tag{2.19}$$

$\xi_{it} \equiv (u_{it} - u_{it-1}) - (\pi_1\lambda_{1it} + \pi_2\lambda_{2it} + \pi_3\lambda_{3it} + \pi_4\lambda_{4it})$ has a conditional expectation of zero by construction. This means that when we assume that we can form consistent estimates of the λ's, we can consistently estimate β as well.

Intuitively, it makes sense that we have four correction terms since the selection indicator in the panel data sample selection model is a combination of the ordered probit model of Dustmann and Schmidt (2000) (leading to a doubly truncated bivariate normal distribution with two selection terms for the lower- and upper threshold) and the bivariate probit model of Rochina-Barrachina (1999) (leading to a singly truncated trivariate normal distribution with two selection terms for the thresholds at time t and $t-1$). The bivariate ordered probit model in our method leads to a doubly truncated trivariate normal distribution with two selection terms for the lower- and upper threshold and two selection terms for the thresholds at time t and $t-1$.

Estimation 2.4.2

In the first step of the estimation procedure we deal with the selection equation. For each $s = \{t, t-1\}$ we estimate the following bivariate ordered probit model

$$h^*_{it-1} = z_{it-1}\gamma_{t-1} + \overline{z_i}\theta_{t-1} + \mu_{it-1} \quad (2.20)$$

$$h^*_{it} = z_{it}\gamma_t + \overline{z_i}\theta_t + \mu_{it} \quad (2.21)$$

$$h_{is} = \begin{cases} 0 \quad \text{(no participation)} & \text{if } h^*_{is} \leq \delta_{1s} \\ 1 \quad \text{(part-time)} & \text{if } \delta_{1s} < h^*_{is} \leq \delta_{2s} \\ 2 \quad \text{(part-time)} & \text{if } \delta_{2s} < h^*_{is} \leq \delta_{3s} \\ \vdots & \\ J \quad \text{(full-time)} & \text{if } \delta_{Js} < h^*_{is} \end{cases} \quad \text{for } s = \{t, t-1\} \quad (2.22)$$

where we choose the number of categories J=5 as our baseline specification.[15] Van Soest (1995) argues that mass points in the number of hours worked exist, because of work hour restrictions in contractual agreements. With J=5, we account for such bunching at full-time work (i.e. 40 hours per week), large part-time work (i.e. 32 hours per week), and small part-time work (i.e. 8-16 hours per week). We provide sensitivity analyses regarding the number of categories in section 2.6. z_{it} includes age dummies for a semi-parametric specification of age effects. Furthermore, we follow Blank (1990b), Ermisch and Wright (1993), Manning and Robinson (2004) and use information regarding marital status, children and other household char-

[15] Franses and Cramer (2010) show that there is no formal statistical testing method for the number of categories in an ordered regression model.

acteristics as exclusion restrictions (z_{it}).[16] By estimating separate models for each s, the age effects are allowed to differ across periods and cohorts. The model takes into account correlation between μ_{it} and μ_{it-1}, denoted in (2.16) to (2.19) by ρ_t. This is important because of the time-constant individual component c_i in $\mu_{it} = c_i + v_{it}$ (explained above).

In the second step we construct the correction terms (2.16) to (2.19) by using the estimates $\hat{a}_{it}$, $\hat{a}_{it-1}$, $\hat{b}_{it}$, $\hat{b}_{it-1}$, and $\hat{\rho}_t$. Next, $\hat{\lambda}_{1it}$, $\hat{\lambda}_{2it}$, $\hat{\lambda}_{3it}$ and $\hat{\lambda}_{4it}$ are used as additional regressors in the wage equation to obtain consistent estimates of β by OLS on the sample of first differences in wages that are observed in t and $t-1$. In order to avoid issues with discontinuous jumps in wages due to labor supply decisions, we select only those with $\Delta h_s = 0$ for the estimation of wages.[17] Similar to Dustmann and Schmidt (2000) we estimate separate wage equations for full-time and part-time work. Furthermore, following Kalwij and Alessie (2007), x includes a flexible semi-parametric specification of age-effects. To avoid the issue with age, period, and cohort effects (captured by the individual-specific effect), as these cannot be identified empirically because the calendar year is equal to the year of birth plus age thereby spanning up the vector space, we leave out period effects in the baseline specification of the wage equation. We leave out period effects as we argue that period effects are less important than age and cohort effects. In the robustness analysis in Section 2.5.2, we show how the results are affected when including period effects, parameterized as a linear time trend or as a function of the unemployment rate. Finally, we use block bootstrapped standard errors clustered at the individual level for inference in the two-stage approach as suggested by Wooldridge (2002).

[16]Our main conclusions are robust to using different exclusion restrictions.

[17]Our main conclusions are robust to allowing for $|\Delta h_s| \leq 1$.

Estimation results 2.5

First stage: labor force participation 2.5.1

The first-stage bivariate ordered probit model is estimated for every combination of t and $t-1$ for $t = \{2002, ..., 2014\}$ for men and women separately. We choose the number of labor supply categories $J = 5$ (as argued in subsection 2.4.2). For men, the bulk of the observations is in the full-time (62%) or non-working category (21%). If men are working part-time, they are often included in the highest part-time category (12%, part-time employment factor ≥ 0.75 and < 1.00). Women are more evenly spread over the different categories. 34% is in the non-working category, 11% in the smallest part-time category (part-time employment factor > 0 and < 0.50), 16% in the third category (≥ 0.50 and < 0.75), 18% in the largest part-time category (≥ 0.75 and < 1.00) and only 21% of women fall in the full-time category.[18]

In Table 2.5 in Appendix 2.C.3 we report the estimation results of the selection equation for the combination of 2001 and 2002 for men and women, respectively. Apart from the direction and significance, the reported coefficients have no direct interpretation and should be interpreted with respect to the estimated parameters $\delta_{j-1,t}$ and $\delta_{j-1,t-1}$ that indicate the thresholds between the J labor supply categories for time t and $t-1$, respectively.

Beginning with the exclusion restrictions, the results show that these variables have large predictive power for both men ($\chi^2 = 216$) and women ($\chi^2 = 1,942$).[19] This holds for both men and women, although we observe differences in which variables are important. For men, we find that only the average individual specific effects or ‘contextual effects’ predict the labor market participation.[20] Men without children and married men are more likely to work (full-time). For women, we observe that both within and contextual variation predict the labor force participation. For women,

[18] For a complete overview of the labor supply categories for all years see Appendix 2.C.1.

[19] The exclusion restrictions are predictive for all combinations of t and $t-1$.

[20] For an explanation of the decomposition into within, between and contextual effects see Bell et al. (2019).

having children, being married or widowed and having a partner past the early retirement age (ERA)[21] are associated with a lower labor force participation. The results show that the likelihood of participation, and especially full-time work, decreases with age. This is true for both men and women and all combinations of t and $t-1$.

Finally, the estimates suggest that the autoregressive nature of labor supply decisions ρ_t is important. Since ρ_t controls for unobserved heterogeneity in the first-stage in the approaches of Rochina-Barrachina (1999) and ours, a high and significant ρ_t can partially explain different results in the application of our approach and Dustmann and Schmidt (2000). Next to first-differences estimation and (non-)parametric assumptions about unobserved heterogeneity. For differences in results between our approach and that of Dustmann and Schmidt (2000), we refer to the robustness analysis in Section 2.5.2.

2.5.2 Second stage: wages

Main estimation results

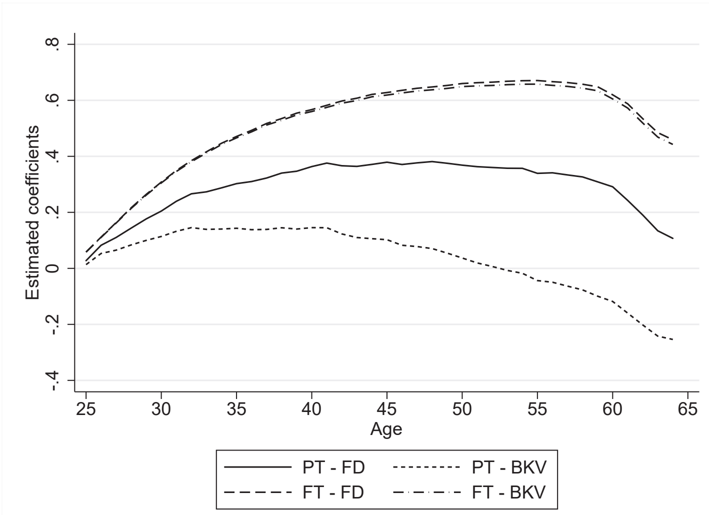
Figure 2.5 presents the age profile of the wages for men and women in part-time and full-time employment. We show the age coefficients without (FD) and with (BKV) the correction terms for selection, which are obtained in the first stage. The first-difference model takes the observed and time-invariant unobserved heterogeneity into account, while our model additionally controls for time-variant unobserved heterogeneity that is related to full-time and part-time work decisions. Taking into account the selection based on time-variant unobserved heterogeneity into part-time and full-time work changes the earnings estimates significantly.

The wage profiles using the FD estimator match the wage descriptives from the previous section well up to the final years prior to retirement. Wages grow over the life-cycle, with the largest increases at younger ages.

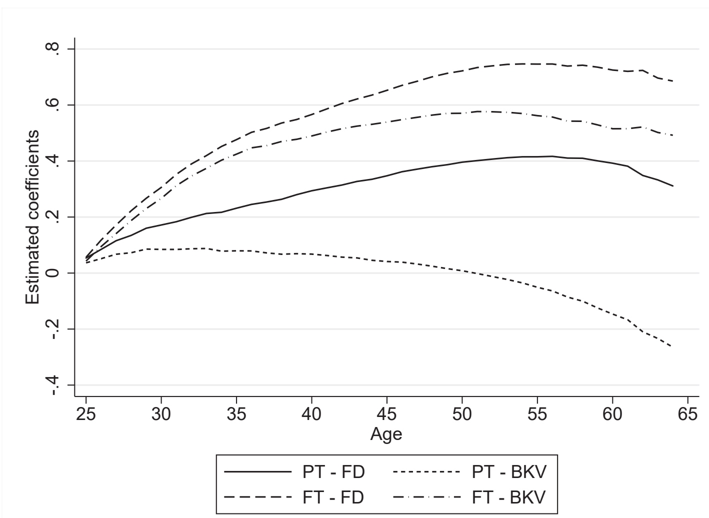
[21] We include a dummy for whether a person's spouse has reached the early retirement age (ERA), because prior empirical literature has shown that reaching the ERA affects own and spouses' labor supply decisions (Been et al. 2021, Stancanelli and Van Soest 2012). The ERA is 62 in many mandatory occupational pension schemes in the Netherlands.

Figure 2.5: Part-time (PT) and full-time (FT) regressions for men (a) and women (b) using first-differences (FD) and our model (BKV)

(a) Estimated coefficients men



(b) Estimated coefficients women



Thereafter, wages only start to decline in the final years prior to retirement. This phenomenon is not observed in the descriptive data and shows the importance of using an FD model. The maximum wage growth is larger for those working in full-time employment (more than 60%) than those in part-time employment (about 40%). These findings are similar for men and women.

Next, we move to the wage profiles obtained using the model that controls for selection into (part-time) work on both observed and unobserved heterogeneity. For men we find positive selection on unobserved individual characteristics in part-time work (p-value=0.0000), but no significant selection into full-time work (p-value=0.9397). This means that men with more affluent characteristics self-select into part-time employment. When men work full-time between the ages of 25 and 64 their estimated wage growth is 69% at the age of 55 (peak) and still about 49% at the age of 64. If, instead, they work part-time, their estimated wage growth is not significantly different from zero. Over the life-cycle, the wage growth of men working full-time is significantly higher than for those working part-time (F-test shows a p-value=0.0000).

For women, we find positive selection based on unobserved characteristics into both part-time work (p-value=0.0000) and full-time work (p-value=0.0000). After correcting for selection, the estimated wage growth is 59% at the age of 51 (peak) and still 51% at the age of 64 for women working full-time. Similar to the results for men, the wage growth when taking selection into account is not significantly different from zero for women working part-time. Over the life-cycle, the wage growth of women in full-time employment is significantly higher than for those in part-time employment (F-test shows a p-value of 0.0000). Overall, the results are comparable for men and women, with the exception that women not only positively select into part-time work, but also positively select into full-time work.

Robustness of the wage profiles

As discussed in section 2.4, when estimating the wage equation we have to make one additional assumption to deal with the collinearity problem of having age, period and cohort effects. Therefore, in our main analysis above we left out the period effects.[22] The robustness of these results are tested by re-estimating models with period effects parameterized as a linear time trend or as a function of the unemployment rate. Next, we test how our model compares to the method proposed by Dustmann and Schmidt (2000). This provides us with insight into the importance of estimation in first-differences with non-parametric assumptions on the unobserved heterogeneity in the wage equation and autoregressive nature of labor supply decisions.[23]

Figure 2.6 in Appendix 2.D shows the estimated age coefficients for the models with period effects for both men and women.[24] We begin with the model with linear period effects.[25] Albeit that age, period and cohort effects cannot be fully identified, this specification enables us to estimate the linear trend in period effects. Both for men and women, we find that the trend in year-to-year changes in wages is negligible, as the concerning coefficients are statistically insignificant. Accordingly, the main conclusions regarding the estimated life-cycle earnings and selection effects for both men and women remain the same. Next, we consider a parametric specification of the model where period effects are a function of the unemployment rate.[26] We find one percentage point increase in the unemployment rate compared to the previous period to be associated with at most a 0.6 percent change in the wages.[27] Again, the general

[22]In Appendix 2.A, we show clear trends in participation, the incidence of part-time work and wages. These trends are probably correlated with age and, therefore, in the case of a model without period effects (partly) absorbed by the age effects.

[23]Dustmann and Schmidt (2000) also use an ordered selection rule in the first-stage, but make parametric assumptions on the unobserved heterogeneity in both the first- and second stage. In comparison, the model proposed in this paper makes no parametric assumptions on the unobserved heterogeneity in the second stage and exploits the autoregressive nature of labor supply decisions similar to Rochina-Barrachina (1999).

[24]To allow for more flexibility, we allow the period effects to differ for those working in part-time and full-time employment in both models.

[25]Since we are estimating first-difference models, this means that we assume the wages to have a constant growth rate over time.

[26]To be more precise, we include the differenced unemployment rate as we are estimating first-difference models in the second stage.

[27]For men in full-time employment, we find one percentage point increase in the unemployment rate compared to the previous period to be associated with a significant 0.6 percent decrease in the wages and no significant association for men in part-time employment. For women, we find one percentage point increase in the unemployment

conclusions regarding the direction and significance of selection remain the same.

Figure 2.7 in Appendix 2.D presents the age estimates for men and women in part-time and full-time employment using the Dustmann and Schmidt (2000) method.[28] From the figure, three general observations stand out. First – as opposed to the previous results – we observe the increases in wages to be largely comparable for men in part-time and full-time employment, even with the correction terms of Dustmann and Schmidt (2000) included. As a result, the life-cycle difference between full-time and part-time wages is negligible. Second, albeit the age estimates of those in both part-time and full-time employment without correction terms show the typical inverted U-shape, the wage profiles of men change drastically when including the correction terms. The wage profiles of men in both part-time and full-time employment continue to go up after the age of 40, indicating substantial negative selection at older ages. Instead of the substantial decreases in wages in the years prior to retirement, the results using the Dustmann and Schmidt (2000) model suggest that wages of men in both part-time and full-time work continue to grow up till retirement. Third, the results for women obtained using the Dustmann and Schmidt (2000) model are comparable to those of the model proposed in this paper, although the magnitude of the selection on unobserved characteristics is smaller. The inclusion of the correction terms using the Dustmann and Schmidt (2000) method shows positive selection on unobserved characteristics into both full-time (p-value=0.0018) as well as part-time employment (p-value=0.0000). The different selection effects, especially for men, show the importance of the estimation in first-differences with non-parametric assumptions on the unobserved heterogeneity in the wage equation and autoregressive nature of labor supply decisions.

rate compared to the year before to be associated with a 0.3 percent decrease (increase) in wages for those in full-time (part-time) employment.

[28]The Dustmann and Schmidt (2000) model is in levels and not in first-differences as it does not exploit the autoregressive nature of participation. Because of this, the age profiles without the correction terms also differ from those estimated using first-differences. However, investigation of this model is still a useful exercise as our main interest lies in how the inclusion of correction terms and the selection effects of the unobserved heterogeneity are affected by the parametric assumptions in the wage equation.

Table 2.1: Selection and number of labor supply categories

	Part-time			Full-time		
J	Selection	χ^2	P-value	Selection	χ^2	P-value
	Men					
RB	Negative	51.4	0.0000	Negative	44.1	0.0000
3	Positive	31.4	0.0000	–	0.3	0.8696
4	Positive	27.9	0.0000	–	0.1	0.9686
5	Positive	30.9	0.0000	–	0.1	0.9397
6	Positive	20.0	0.0000	–	0.1	0.9436
7	Positive	13.0	0.0112	–	0.3	0.8766
8	Positive	24.5	0.0001	–	0.3	0.8645
	Women					
RB	–	0.2	0.9198	Negative	15.1	0.0005
3	Negative	24.9	0.0001	Positive	61.3	0.0000
4	Negative	63.5	0.0000	Positive	66.3	0.0000
5	Positive	93.1	0.0000	Positive	80.1	0.0000
6	Positive	88.7	0.0000	Positive	81.7	0.0000
7	Positive	69.5	0.0000	Positive	77.8	0.0000
8	Positive	125.7	0.0000	Positive	96.8	0.0000

Binary versus ordered selection 2.6

In this section, we investigate the importance of taking the selection in the intensive margin of labor supply into account, as compared to a binary selection rule (i.e. as proposed by Rochina-Barrachina (1999)). As argued in section 2.4, the choice of the number of labor supply categories in our model (J) is arbitrary to some extent and is a trade-off between more categories versus more observations per category. Hence, to get an idea of how important the choice for J is for conclusions regarding selection effects, we present Table 2.1 in which we show the direction and significance of the selection terms for different choices of J. We restrict our analysis to $2 \leq J \leq 8$ to make sure we have a sufficient number of observations per category. In theory, $J > 8$ should be possible as long as there is a sufficient number of observations per category. Recall, in our main analysis we use J=5, allowing for three different part-time employment categories.

We find two interesting patterns regarding selection and choices for J in Table 2.1. Firstly, for $J > 2$ (ordered selection), our proposed method produces different conclusions regarding the existence and direction of selection than for $J = 2$ (binary selection). Hence, including unobserved information regarding the intensive labor supply decision is important compared to information on selection in the extensive margin of labor supply. The results with $J = 2$ suggest negative selection among both part-time and full-time employed men, whereas we find positive or no selection effects among these groups for $J > 2$, respectively. For women, the results of $J = 2$ show no selection effects for part-time employed women whereas we find evidence in favor of selection for $J > 2$, albeit the direction of the selection bias depends on J. For women working full-time, we find negative selection for $J = 2$ and positive selection for $J > 2$.

Secondly, we find that conclusions regarding selection are consistent across $J > 2$ among men, but not among women. For men, we find that adding information beyond $J = 3$ does not change the results for both part-time and full-time employed men. Among full-time employed women, conclusions regarding selection are consistent across $J > 2$. For part-time employed women, however, a less consistent picture arises when analyzing selection for $J > 2$. For $3 \leq J \leq 4$, we find negative selection. For $5 \leq J \leq 8$, we find positive selection. This switching of the direction of selection from $J = 4$ to $J = 5$ is most likely a consequence of the increased unobserved information allowed for by a larger J. Logically, this tends to be especially important among part-time employed women since there are relatively many women working part-time, both in relatively small and large part-time jobs (see Table 2.3 in the appendix). In contrast, part-time working men can often be found in relatively large part-time jobs which makes the additional information from $J > 3$ less important than for women.

Given the analyses in Table 2.1, we conclude that allowing for part-time employment is important for conclusions regarding selection, but choosing the number of categories $J > 2$ is of less importance as results are largely consistent. However, applied researchers should be aware that the additional information from a larger J is most likely important for the analysis of women in part-time employment.

2.7 Conclusion

To estimate correct earnings profiles over the life-cycle, we argue that non-random selection into full-time and part-time work contains relevant information on unobserved heterogeneity. Therefore, we propose a new panel data sample selection model that conditions on selection into both full-time and part-time work. We build on the method of Rochina-Barrachina (1999) and extend her method by allowing for an ordered instead of binary selection rule which allows us to differentiate between full-time and part-time work. In this way, we extend the method by Rochina-Barrachina (1999) in a similar way as Dustmann and Schmidt (2000) extended Wooldridge (1995). The main advantage of Rochina-Barrachina (1999) over Wooldridge (1995) is that no parametric assumptions about the unobserved heterogeneity in wages and the decision to work are needed.

Using administrative data from the Netherlands, where part-time work is highly prevalent, we show that taking into account non-random selection into (part-time) work changes the earnings estimates significantly. For men, we find no selection into full-time work which suggests that selecting full-time working prime age males in models of earnings dynamics does not lead to biased estimates. Hence, using full-time working men without selection correction, as in Lagakos et al. (2018) for example, is justified by our results (though we particularly focus on Dutch men, who are not considered by Lagakos et al. (2018)). However, results are unlikely to be representative for other groups among which part-time working men for whom we find positive selection in part-time work. This implies that men with relatively affluent characteristics choose part-time work and that part-time wages are overestimated if such selection is not taken into account. For women, we find positive selection into both part-time and full-time work. Moreover, we show with our new panel data estimator that it is important to distinguish between part-time and full-time employment, as taking into account labor supply decisions at the extensive margin only – like in Rochina-Barrachina (1999) – leads to different conclusions with respect to the existence and direction of selection. Hence, we conclude that part-time employment entails additional information on unobserved characteristics that are import in the estimation of wage profiles.

Applying our method to estimate life-cycle earnings profiles, we show that correcting for selection also results in different shapes of the earnings profiles compared to regular first-differences estimates. With our proposed method, we find that earnings in full-time employment peak later in the life-cycle than earnings in part-time employment. This is true for both men and women. Additionally, these differences are amplified when correcting for selection into full-time and part-time employment.

Our study has important implications for both academics and policy. For academics, our proposed method is useful for several applications, such as 1) the estimation of part-time wage penalties and 2) testing for the existence of selection among full-time working prime age men who are generally selected in earnings models.[29] Additionally, our model is also useful in other contexts where the selection decision is ordered, e.g. the number of children or subjective health outcomes. For policy, applying our method to administrative earnings data from the Netherlands, we show that part-time work has large effects on life-time earnings and, hence, on the accumulation of savings, pensions, and wealth.

[29] Among others, Baker (1997), Baker and Solon (2003), Daly et al. (2022), Gottschalk and Moffitt (1994), Guvenen (2009), Heathcote et al. (2010), Lagakos et al. (2018), Lillard and Weiss (1979), Lillard and Willis (1978), Meghir and Pistaferri (2004, 2010), Moffitt and Gottschalk (2012), Pischke (1995), Storesletten et al. (2004).

Wage descriptives over time 2.A

Columns 3 to 10 in Table 2.2 present full-time and part-time wage rates, and (part-time) participation rates for men and women, respectively. As expected, participation rates are higher for men than for women. However, both declining participation rates for men and increasing participation rates for women make the difference in participation rates between men and women smaller over time, from 20%-points in 2001 to 5%-points in 2014. For both men and women part-time employment (conditional on participation) has increased over time, with the most substantial growth among men. Despite this, men still had much lower part-time employment rates (27%) than women (71%) in 2014.

Next we look at full-time and part-time wages, where we increased the part-time wage using the part-time employment factor to match the full-time wages. From the wage statistics, four general observations stand out. First, wages are on average higher for men than for women. This holds for both full-time and part-time wages in all sample years. Second, full-time wages are on average higher than part-time wages. Similarly to the previous observation, this holds for both men and women in all sample years. Third, the gender wage gap (column 2) has declined between 2001 and 2014.[30] In turn, this is the result of the faster increase in part-time employment of men compared to women, declining (part-time) wages for men and increasing (full-time) wages for women.

[30]Again, we observe a discontinuity around 2006. When we focus on the two separate time period, i.e. 2001-2005 and 2006-2014, the cumulative decline is even more pronounced.

Table 2.2: Trends in participation and wages

Year	Men				Women			
	Average FT wage	Average PT wage	Part-time[a] (%)	Partici-pation (%)	Average FT wage	Average PT wage	Part-time[a] (%)	Partici-pation (%)
2001	46,536	43,765	14	80	38,850	36,923	64	60
2002	46,646	43,915	15	80	39,375	37,764	64	61
2003	47,255	44,793	15	79	39,922	37,731	65	62
2004	47,549	44,715	16	78	40,596	38,212	66	62
2005	47,397	46,033	17	78	40,680	38,409	67	62
2006	48,092	43,570	26	78	40,968	35,502	68	64
2007	47,610	42,763	26	79	41,102	35,972	68	66
2008	48,318	42,252	28	79	41,587	35,861	67	67
2009	48,419	42,848	27	78	42,205	36,629	68	67
2010	48,636	41,721	24	76	42,297	37,072	68	67
2011	48,120	41,857	26	77	42,663	36,619	69	69
2012	47,596	41,278	26	77	42,250	36,433	69	70
2013	47,282	39,716	26	76	42,095	36,048	70	70
2014	47,805	40,147	27	75	43,024	36,171	71	70

[a] For persons who actually work.

2.B Derivation of correction terms

Following the method of the two-step approach proposed by Heckman (1976, 1979), we work out (2.10) to obtain correction terms, that can be added as additional regressors to the main equation (the wage equation). Rochina-Barrachina (1999) also extends Heckman's sample selection technique to the case where one correlated selection rule in two different time periods generates the sample. In addition, we allow an ordered selection rule instead of a binary selection indicator.

Equation 2.10 contains the first moment of a doubly truncated trivariate normal distribution (where $(u_{it} - u_{it-1})$ is not truncated[31] and $\frac{\mu_{it-1}}{\sigma_{\mu t-1}}$ and $\frac{\mu_{it}}{\sigma_{\mu t}}$ are doubly truncated). For the sake of convenience, in the remainder of this Appendix we denote $w_1 = u_{it} - u_{it-1}$, $w_2 = \frac{\mu_{it-1}}{\sigma_{\mu t-1}}$ and $w_3 = \frac{\mu_{it}}{\sigma_{\mu t}}$. Following Manjunath and Wilhelm (2012), the trivariate truncated normal density is defined as

$$\phi_{\alpha\Sigma}(w_1, w_2, w_3) = \begin{cases} \frac{\phi_{\Sigma}(w_1,w_2,w_3)}{\alpha} & \text{for } a_{it-1} \leq w_2 < b_{it-1} \text{ and } a_{it} \leq w_3 < b_{it} \\ 0 & \text{otherwise} \end{cases}$$

[31] Boundaries of $-infty$ and $infty$

where $a_{it-1}, a_{it}, b_{it-1}$ and b_{it} are defined in (2.11) to (2.14). α denotes the fraction after truncation ($= P(a_{it-1} \leq w_2 < b_{it-1}$ and $a_{it} \leq w_3 < b_{it})$), and ϕ_{Σ} the normal density with expectations of zero and covariance matrix Σ.

To calculate the first moment of w_1, we use the moment generating function (*m.g.f*) of the doubly truncated trivariate normal distribution. We take the derivative with respect to t_1 and evaluate the function in $\boldsymbol{t} = 0$. The moment generating function is defined as the threefold integral of the form

$$m(\boldsymbol{t}) = E(e^{\boldsymbol{t}'\boldsymbol{w}}) \tag{2.23}$$

$$= \frac{1}{\alpha(2\pi)^{3/2}|\Sigma|^{1/2}} \int_{\mathbf{a}}^{\mathbf{b}} exp\left(-\frac{1}{2}\boldsymbol{w}'\boldsymbol{\Sigma}^{-1}\boldsymbol{w} - 2\boldsymbol{t}'\boldsymbol{w}\right) d\boldsymbol{w} \tag{2.24}$$

For the derivation of the first derivative of the m.g.f. with regard to t_1 we refer to (7)–(10) in Manjunath and Wilhelm (2012):

$$\frac{\partial m(\boldsymbol{t})}{\partial t_1} = e^{\frac{1}{2}\boldsymbol{t}'\boldsymbol{\Sigma}\boldsymbol{t}} \frac{\partial \Phi_{\alpha\boldsymbol{\Sigma}}}{\partial t_1} + \Phi_{\alpha\boldsymbol{\Sigma}} \frac{\partial e^{\frac{1}{2}\boldsymbol{t}'\boldsymbol{\Sigma}\boldsymbol{t}}}{\partial t_1} \tag{2.25}$$

where

$$\Phi_{\alpha\boldsymbol{\Sigma}} = \frac{1}{\alpha(2\pi)^{3/2}|\Sigma|^{1/2}} \int_{\boldsymbol{a}-\boldsymbol{\Sigma}t}^{\boldsymbol{b}-\boldsymbol{\Sigma}t} \exp\left(-\frac{1}{2}\boldsymbol{w}'\boldsymbol{\Sigma}^{-1}\boldsymbol{w}\right) d\boldsymbol{w}. \tag{2.26}$$

In (2.26) $\boldsymbol{a} = (-\infty, a_{it-1}, a_{it})$ and $\boldsymbol{b} = (\infty, b_{it-1}, b_{it})$. In (2.25) the last term can be simplified as

$$\frac{\partial e^{\frac{1}{2}\boldsymbol{t}'\boldsymbol{\Sigma}\boldsymbol{t}}}{\partial t_1} = e^{\frac{1}{2}\boldsymbol{t}'\boldsymbol{\Sigma}\boldsymbol{t}} \left(t_1\sigma_1^2 + t_2\sigma_{12} + t_3\sigma_{13}\right) \tag{2.27}$$

Furthermore, the last part of the first term of (2.25) can be rewritten as

$$\frac{\partial \Phi_{\alpha\boldsymbol{\Sigma}}}{\partial t_1} = \frac{\partial}{\partial t_1} \int\limits_{\boldsymbol{a}-\boldsymbol{\Sigma}t}^{\boldsymbol{b}-\boldsymbol{\Sigma}t} \phi_{\alpha\boldsymbol{\Sigma}}(\boldsymbol{w})d\boldsymbol{w} \tag{2.28}$$

After applying the Leibniz's rule for differentiation under the integral sign and rewriting the equation this becomes

$$\begin{aligned}
\frac{\partial \Phi_{\alpha\boldsymbol{\Sigma}}}{\partial t_1} = \\
&- \sigma_1^2 \int\limits_{a_2^*}^{b_2^*} \int\limits_{a_3^*}^{b_3^*} \phi_{\alpha\boldsymbol{\Sigma}}(b_1^*, w_2, w_3) dw_3 dw_2 + \sigma_1^2 \int\limits_{a_2^*}^{b_2^*} \int\limits_{a_3^*}^{b_3^*} \phi_{\alpha\boldsymbol{\Sigma}}(a_1^*, w_2, w_3) dw_3 dw_2 \\
&- \sigma_{12} \int\limits_{a_1^*}^{b_1^*} \int\limits_{a_3^*}^{b_3^*} \phi_{\alpha\boldsymbol{\Sigma}}(w_1, b_2^*, w_3) dw_3 dw_1 + \sigma_{12} \int\limits_{a_1^*}^{b_1^*} \int\limits_{a_3^*}^{b_3^*} \phi_{\alpha\boldsymbol{\Sigma}}(w_1, a_2^*, w_3) dw_3 dw_1 \\
&- \sigma_{13} \int\limits_{a_1^*}^{b_1^*} \int\limits_{a_2^*}^{b_2^*} \phi_{\alpha\boldsymbol{\Sigma}}(w_1, w_2, b_3^*) dw_2 dw_1 + \sigma_{13} \int\limits_{a_1^*}^{b_1^*} \int\limits_{a_2^*}^{b_2^*} \phi_{\alpha\boldsymbol{\Sigma}}(w_1, w_2, a_3^*) dw_2 dw_1
\end{aligned} \tag{2.29}$$

where $[a_1^* \quad a_2^* \quad a_3^*]' = \boldsymbol{a}^* = \boldsymbol{a} - \boldsymbol{\Sigma t}$ and $[b_1^* \quad b_2^* \quad b_3^*]' = \boldsymbol{b}^* = \boldsymbol{b} - \boldsymbol{\Sigma t}$. Taking the terms together and evaluating the derivative $\frac{\partial m(\boldsymbol{t})}{\partial t_1}$ in $\boldsymbol{t} = 0$ gives us the first moment of w_1

$$\begin{aligned}
\mathrm{E}(w_1 | a_{it-1} \leq w_2 < b_{it-1} \text{ and } a_{it} \leq w_3 < b_{it}) = \\
&- \sigma_{12} \frac{\phi(b_{it-1})}{\alpha} \left[\Phi\left(\frac{b_{it} - \rho b_{it-1}}{\sqrt{1-\rho^2}} \right) - \Phi\left(\frac{a_{it} - \rho b_{it-1}}{\sqrt{1-\rho^2}} \right) \right] \\
&+ \sigma_{12} \frac{\phi(a_{it-1})}{\alpha} \left[\Phi\left(\frac{b_{it} - \rho a_{it-1}}{\sqrt{1-\rho^2}} \right) - \Phi\left(\frac{a_{it} - \rho a_{it-1}}{\sqrt{1-\rho^2}} \right) \right] \\
&- \sigma_{13} \frac{\phi(b_{it})}{\alpha} \left[\Phi\left(\frac{b_{it-1} - \rho b_{it}}{\sqrt{1-\rho^2}} \right) - \Phi\left(\frac{a_{it-1} - \rho b_{it}}{\sqrt{1-\rho^2}} \right) \right] \\
&+ \sigma_{13} \frac{\phi(a_{it})}{\alpha} \left[\Phi\left(\frac{b_{it-1} - \rho a_{it}}{\sqrt{1-\rho^2}} \right) - \Phi\left(\frac{a_{it-1} - \rho a_{it}}{\sqrt{1-\rho^2}} \right) \right]
\end{aligned} \tag{2.30}$$

where ρ is the correlation coefficient of w_2 and w_3, and $\alpha = \Phi_2(b_{it-1}, b_{it}, \rho) - \Phi_2(a_{it-1}, a_{it}, \rho)$.

Estimation of the selection equation 2.C

Labor supply categories 2.C.1

Here we describe the distribution of workers over the five labor supply categories ($J = 5$) for men and women, respectively. For men, the bulk of the observations is in the full-time (62%) or the non-working category (21%). Only 2% and 3% of the men fall in the two smallest part-time categories (part-time employment factor > 0 and < 0.50, and ≥ 0.50 and < 0.75, respectively) and 12% in the highest part-time category (part-time employment factor ≥ 0.75 and < 1.00). The share of men in the full-time category is declining over time from 70 percent in 2001 to 56 percent in 2014. The categories that consequently show the largest increases are the non-working and the largest part-time work categories.

Women are more evenly spread over the different categories. 34% is in the non-working category, 11% in the smallest part-time category (part-time employment factor > 0 and < 0.50), 16% in the third category (part-time employment factor ≥ 0.50 and < 0.75), 18% in the largest part-time category (part-time employment factor ≥ 0.75 and < 1.00). Only 21% of women work full-time and fall in the final category. As opposed to men, the share of women in the full-time employment category is relatively stable over time. The largest changes for women are observed in the non-working and the larger part-time work categories. The share of women that is non-working has decreased from 40 percent in 2001 to 30 percent in 2014, which resulted in more women in the two largest part-time categories.

Table 2.3: Distribution of men and women over the 5 labor supply categories over time

	Men					Women				
Year	Non-working	0 < fte <0.5	0.5 ≤ fte <0.75	0.75 ≤ fte <1	Full-time	Non-working	0 < fte <0.5	0.5 ≤ fte <0.75	0.75 ≤ fte <1	Full-time
2001	0.185	0.021	0.026	0.070	0.699	0.397	0.110	0.131	0.143	0.218
2002	0.189	0.021	0.026	0.071	0.693	0.381	0.113	0.139	0.147	0.220
2003	0.196	0.024	0.025	0.074	0.681	0.378	0.112	0.143	0.147	0.220
2004	0.205	0.023	0.029	0.076	0.668	0.377	0.105	0.153	0.153	0.212
2005	0.211	0.027	0.030	0.076	0.656	0.372	0.112	0.148	0.158	0.210
2006	0.206	0.022	0.030	0.151	0.591	0.347	0.110	0.154	0.179	0.210
2007	0.198	0.021	0.029	0.156	0.596	0.335	0.103	0.160	0.192	0.210
2008	0.197	0.023	0.028	0.174	0.578	0.321	0.104	0.159	0.195	0.221
2009	0.209	0.022	0.029	0.159	0.581	0.316	0.105	0.162	0.198	0.219
2010	0.220	0.022	0.030	0.136	0.592	0.315	0.102	0.168	0.192	0.222
2011	0.218	0.023	0.033	0.150	0.576	0.307	0.102	0.171	0.209	0.212
2012	0.219	0.025	0.031	0.150	0.575	0.298	0.101	0.177	0.209	0.215
2013	0.229	0.024	0.035	0.139	0.572	0.295	0.101	0.184	0.211	0.210
2014	0.232	0.022	0.033	0.152	0.562	0.294	0.098	0.181	0.220	0.208
Total	0.208	0.023	0.030	0.123	0.616	0.338	0.106	0.159	0.182	0.215

2.C.2 Transitions in labor supply categories

Table 2.4 describes the year-to-year transitions in labor supply categories for $J = 5$. The diagonal of the transition matrix represents individuals who remained in the same labor supply category from time $t-1$ to t (i.e. $\Delta h_s = 0$). Both men and women exhibit strong persistence in certain categories. Specifically, the probability of staying in non-employment ($h_t = 1$) is approximately 0.98. Similarly, the probability of staying in full-time employment ($h_t = 5$) is very high. Among men, the persistence in full-time work is particularly strong at 0.91, while among women it is also notable at 0.84. Persistence in the part-time categories ($h_t = 2, 3, 4$) is lower compared to non-employment and full-time employment but still substantial, especially among women.

As elaborated in more detail in Section 2.3, the administrative records provide comprehensive information regarding (labor) income and the part-time factor but do not include details about the distribution of working hours throughout the calendar year. This paper compares part-time and full-time wages. Transitions between different labor supply categories (i.e., $\Delta h_s \geq 1$), however, are likely driven by changes in the extensive margin rather than the intensive margin (e.g. people becoming unemployed or starting a job during the calendar year). Given this and the small absolute and relative numbers, we exclude them from the main analysis.

Table 2.4: Year-to-year transitions (fractions) in labor supply categories of men and women

Men	*t*					
$t-1$	Non-working	0 < fte <0.5	$0.5 \leq$ fte <0.75	$0.75 \leq$ fte <1	Full-time	N
Non-working	0.979	0.003	0.003	0.005	0.010	49,507
0 < fte <0.5	0.064	0.580	0.147	0.110	0.010	7,761
$0.5 \leq$ fte <0.75	0.039	0.086	0.478	0.233	0.164	7,086
$0.75 \leq$ fte <1	0.023	0.013	0.046	0.593	0.325	32,393
Full-time	0.013	0.003	0.007	0.067	0.911	173,203
Women	*t*					
$t-1$	Non-working	0 < fte <0.5	$0.5 \leq$ fte <0.75	$0.75 \leq$ fte <1	Full-time	N
Non-working	0.989	0.005	0.003	0.002	0.002	87,297
0 < fte <0.5	0.027	0.775	0.152	0.033	0.014	26,318
$0.5 \leq$ fte <0.75	0.015	0.079	0.761	0.118	0.028	43,104
$0.75 \leq$ fte <1	0.010	0.013	0.102	0.737	0.139	49,167
Full-time	0.010	0.005	0.022	0.125	0.839	59,420

2.C.3 First-stage regression results

Table 2.5: Estimation results selection equation for men and women

	men				women			
	t=2002		t-1=2001		t=2002		t-1=2001	
	Coef.	S.e.	Coef.	S.e.	Coef.	S.e.	Coef.	S.e.
Age 25	–		-0.37**	0.17	–		-0.05	0.16
Age 26	-0.44***	0.17	-0.35**	0.15	-0.15	0.16	-0.10	0.11
Age 27	-0.41***	0.15	-0.52***	0.15	-0.13	0.12	-0.37***	0.14
Age 28	-0.58***	0.15	-0.61***	0.15	-0.40***	0.14	-0.39***	0.13
Age 29	-0.64***	0.15	-0.44***	0.15	-0.54***	0.13	-0.45***	0.14
Age 30	-0.56***	0.16	-0.66***	0.15	-0.54***	0.15	-0.63***	0.14
Age 31	-0.79***	0.15	-0.63***	0.15	-0.70***	0.15	-0.67***	0.14
Age 32	-0.75***	0.16	-0.98***	0.16	-0.80***	0.15	-0.91***	0.15
Age 33	-1.08***	0.16	-1.03***	0.16	-1.03***	0.16	-0.96***	0.15
Age 34	-1.13***	0.17	-1.11***	0.17	-1.10***	0.16	-1.25***	0.16
Age 35	-1.28***	0.17	-1.27***	0.17	-1.33***	0.17	-1.33***	0.17
Age 36	-1.37***	0.17	-1.52***	0.17	-1.47***	0.17	-1.49***	0.18
Age 37	-1.60***	0.18	-1.61***	0.18	-1.59***	0.18	-1.48***	0.18
Age 38	-1.73***	0.18	-1.55***	0.19	-1.61***	0.19	-1.54***	0.19
Age 39	-1.68***	0.19	-1.70***	0.19	-1.70***	0.20	-1.55***	0.19
Age 40	-1.87***	0.19	-1.93***	0.20	-1.71***	0.20	-1.71***	0.20
Age 41	-2.03***	0.20	-2.00***	0.20	-1.86***	0.21	-1.73***	0.20
Age 42	-2.19***	0.20	-2.10***	0.20	-1.86***	0.21	-1.58***	0.21
Age 43	-2.27***	0.20	-2.22***	0.21	-1.73***	0.22	-1.63***	0.22
Age 44	-2.34***	0.21	-2.21***	0.21	-1.79***	0.22	-1.75***	0.22
Age 45	-2.32***	0.22	-2.50***	0.21	-1.94***	0.23	-1.78***	0.23
Age 46	-2.59***	0.22	-2.48***	0.22	-1.99***	0.23	-1.74***	0.23
Age 47	-2.62***	0.22	-2.58***	0.23	-2.01***	0.24	-1.84***	0.24
Age 48	-2.72***	0.23	-2.66***	0.23	-1.99***	0.25	-1.80***	0.24
Age 49	-2.86***	0.23	-2.85***	0.23	-2.06***	0.25	-1.77***	0.24
Age 50	-2.99***	0.24	-2.76***	0.24	-1.97***	0.25	-1.70***	0.25
Age 51	-2.96***	0.24	-2.80***	0.24	-1.95***	0.26	-1.88***	0.25
Age 52	-2.98***	0.25	-2.80***	0.25	-2.08***	0.26	-1.81***	0.26
Age 53	-2.98***	0.25	-2.96***	0.25	-1.97***	0.26	-1.93***	0.26
Age 54	-3.07***	0.25	-3.13***	0.25	-2.15***	0.27	-1.98***	0.26
Age 55	-3.25***	0.25	-3.16***	0.26	-2.17***	0.27	-1.94***	0.27
Age 56	-3.36***	0.26	-3.28***	0.26	-2.16***	0.27	-2.00***	0.27
Age 57	-3.43***	0.26	-3.36***	0.26	-2.29***	0.28	-2.19***	0.28
Age 58	-3.59***	0.26	-3.67***	0.28	-2.46***	0.29	-2.28***	0.29
Age 59	-3.89***	0.28	-3.78***	0.28	-2.55***	0.29	-2.26***	0.30
Age 60	-4.06***	0.28	-4.22***	0.29	-2.50***	0.31	-2.27***	0.32
Age 61	-4.60***	0.29	-4.39***	0.30	-2.69***	0.33	-2.71***	0.33
Age 62	-4.83***	0.30	-4.83***	0.31	-3.28***	0.34	-3.27***	0.38
Age 63	-5.09***	0.32	-5.02***	0.36	-3.52***	0.39	-3.65***	0.47
Age 64	-4.98***	0.36			-3.74***	0.48		
Children	0.02	0.02	0.01	0.02	-0.27***	0.02	-0.25***	0.02
Single	–		–		–		–	
Married	0.00	0.04	0.02	0.03	-0.30***	0.04	-0.29***	0.04
Divorced	-0.03	0.06	-0.05	0.06	-0.15***	0.06	-0.16***	0.05
Widowed	-0.04	0.16	-0.06	0.16	-0.39***	0.09	-0.27***	0.09
Partner ERA	0.10*	0.06	0.05	0.06	0.12***	0.04	0.03	0.04
Children (average)	-0.15***	0.04	-0.14***	0.04	-0.40***	0.04	-0.39***	0.04
Single (average)	–		–		–		–	

Continued on next page

Table 2.5 – continued from previous page

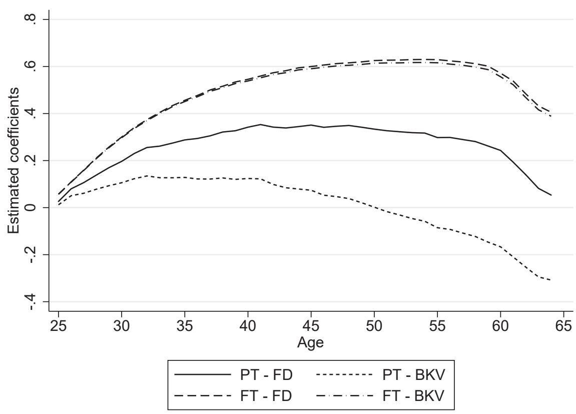
	Men				Women			
	t=2002		t-1=2001		t=2002		t-1=2001	
	Coef.	S.e.	Coef.	S.e.	Coef.	S.e.	Coef.	S.e.
Married (average)	0.36***	0.05	0.38***	0.04	-0.34***	0.05	-0.33***	0.05
Divorced (average)	0.02	0.02	0.06	0.07	-0.05	0.07	-0.05	0.06
Widowed (average)	0.13	0.16	0.23	0.17	-0.66***	0.11	-0.76***	0.10
Partner ERA (average)	-0.18**	0.09	0.18**	0.09	-0.60***	0.07	-0.52***	0.06
χ^2-stat $\bar{z}_i$	2,011***				2,847***			
χ^2-stat $\bar{z}_i$ excl. age dummies	103***				390***			
χ^2-stat exclusion restrictions	216***				1,942***			
δ_{1s}	3.35**	1.43	3.09**	1.37	1.68	1.48	0.83	1.51
δ_{2s}	3.43**	1.43	3.18**	1.37	2.07	1.48	1.23	1.51
δ_{3s}	3.53**	1.43	3.29**	1.37	2.51*	1.48	1.65	1.51
δ_{4s}	3.74***	1.43	3.50**	1.37	2.99**	1.48	2.12	1.51
ρ_t	0.97***	0.00			0.95***	0.00		
Obs.	20,985				19,510			
χ^2	2,037				4,458			

Note: $\bar{z}_i$ includes individual time averages of all age dummies, marital status dummies, children dummy and the variable indicating whether having a partner past the early retirement age (ERA). The different parameters for δ_{Js} indicate the thresholds between the $J = 5$ labor supply categories. ρ_t indicates the correlation between the error terms at time t and $t - 1$. Standard errors are robust and clustered at the individual level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

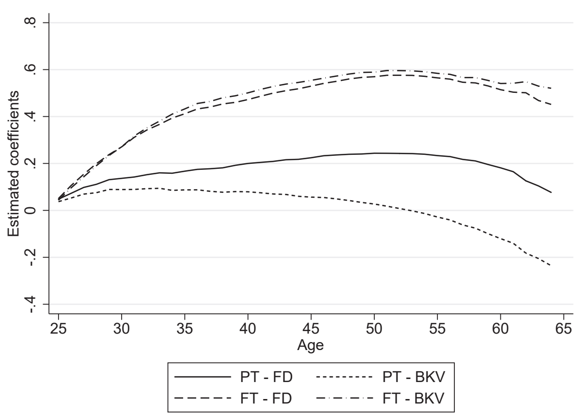
2.D Robustness of the wage equation

Figure 2.6: Part-time (PT) and full-time (FT) regressions using first-differences (FD) and our model (BKV) controlling for linear period effects and unemployment rates

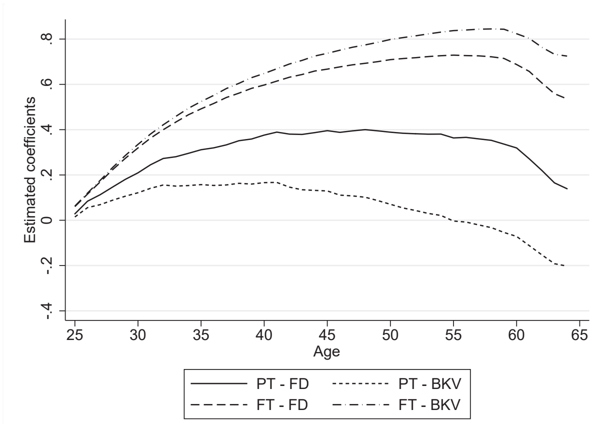
(a) Linear period effects, men



(b) Linear period effects, women



(c) Unemployment rates, men



(d) Unemployment rates, women

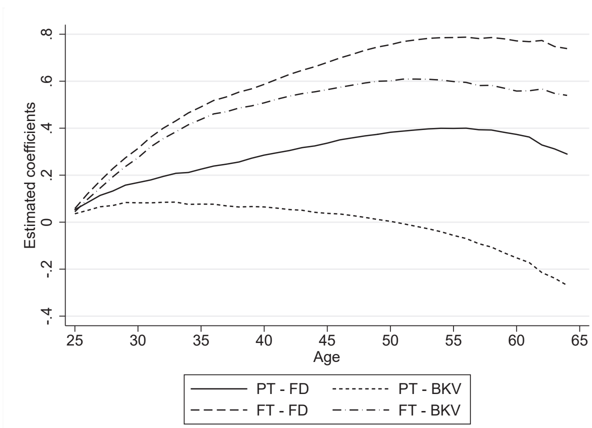
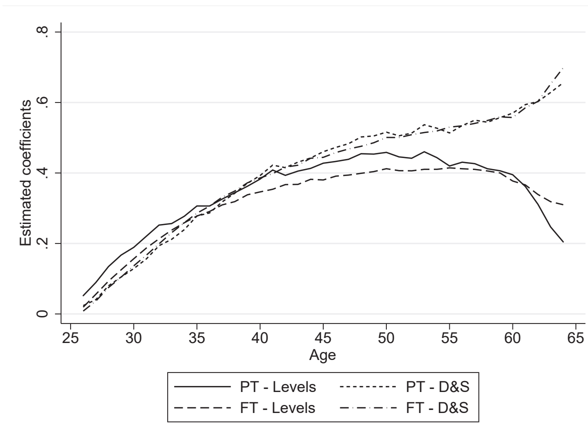


Figure 2.7: Part-time (PT) and full-time (FT) regressions for men (a) and women (b) using levels and Dustmann and Schmidt (2000) approach

(a) Estimated coefficients men



(b) Estimated coefficients women