“To Shape the Future”: The Effects of Initial Economic Conditions at the Time of Entry into the Labor Force on Individuals’ Subsequent Labor Market Performance

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Abstract

We study how economic conditions at the time individuals enter into the labor market affect their wages in the short- and in the long-run. We use a large and representative sample of men entering the Austrian labor market between 1978 and 2000, covering both period of low and high unemployment and allowing us to track them up to 27 years. In order to minimize the problem of endogenous entry into the labor market we focus on individuals with lower educational attainment as they are unlikely to postpone their entry into the labor force by staying longer in school in times of high unemployment. However, we additionally provide empirical evidence on the relation between the local unemployment rate at the likelihood of entering into the labor force and the duration of schooling. The empirical analysis proceeds in three steps. We first estimate the immediate impact of labor market conditions on starting wages. Second, we estimate the long-run impact of these conditions on individuals’ wage profiles. Consistent with previous evidence, we find a robust negative effect of unfavorable conditions on starting wages. This effect is largest for higher wages implying a wage compression in times of high unemployment. Moreover, we also find persistent effects of initial economic conditions on subsequent wages. However, these effects seem to fade away as the years go by. Finally, we look at individuals’ patterns of mobility across firms, industries and regions which coincide with the predicted catch-up effect in wages.

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Keywords: Wage profiles, entry into the labor force, starting wages, wage contracts, persistence of shocks, unemployment, mobility

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1 Introduction

Existing empirical literature shows the importance of the early working years in terms of subsequent labor market performance.[1] However, there are macroeconomic risks beyond an individual's control which may disrupt the formative period of a young worker. For instance, the job market conditions prevailing at the time of labor market entry provide an element of randomness which every individual moving from school to work faces. While some immediate disadvantage from unfavorable entry conditions seems quite obvious, because a rise in the unemployment rate may lead to an increase of mismatches between workers and jobs, it is less apparent whether long term consequences for a workers' career will emerge. On the one hand, the early working years are found to be characterized by high job mobility, suggesting that workers may recover from initial disadvantages by switching to better jobs as soon as the economy recovers. On the other hand, however, bad entry conditions may translate into sustained wage disadvantages if early years of individuals' labor market career are especially crucial because for example the early years are more training-intensive than later years.

This paper aims to study the impact of business cycle fluctuations on workers' labor market careers. Specifically, we estimate the impact of the unemployment rate prevailing at the time individuals first enter into the labor market on their starting wages as well as on their subsequent wage profiles. We thus provide estimates on long-run effects of exogenous labor market shocks and thus are able to shed light on how the pattern of persistence looks like. We further bring into focus individuals' mobility as an important mechanism of adjustment by analyzing how workers move between firms, industries and regions over the business cycle. Previous research provides convincing evidence on short-run effects of labor market shocks on individuals' earnings.[2] However, there is growing empirical evidence showing that labor market shocks may have quite persistent effects. Such evidence is important not only as it provides estimates on the costs of labor market shocks but also as it is informative in terms of wage setting mechanisms in real labor markets. Beyond that, evidence on how labor market shocks propagate and how workers adjust to such shocks is revealing itself. In order to minimize the problem of endogenous timing of labor market entry we focus on less skilled individuals as they are less likely to manipulate the time of entry by staying longer in school in times of high unemployment. We provide in addition several empirical checks on the relationship between the labor market condition and the timing of entry to show that our results are not mainly driven by selection and resulting compositional effects.

Although empirical literature looking at long term effects of such labor market shocks

[1] For example, Murphy and Welch (1990) estimate that almost 80% of all wage increases accrue to the first ten years of one's labor market career. Likewise, job changes are considerably more likely at the beginning of a worker's career (Topel and Ward, 1992). Furthermore, there is some related work showing that the early years of the labor market career are relevant for understanding the gender wage gap (e.g. Light and Ureta, 1995).

[2] A prominent strand in the literature provides evidence of short-run wage effects by showing the existence of a wage curve. That means, employees that work in areas with high unemployment, other things being constant, earn less than those who face low unemployment. See Blanchflower and Oswald (1990) and the discussion by Card (1995).

is growing, there have been yet - to the best of our knowledge - only four closely related studies. Oreopoulos *et al.* (2006, 2008) explore effects on earnings and mobility for Canadian college graduates entering the labor market during a recession. Relying on matched university-employer-data of graduates from 1982 to 1999, they find a significant initial wage penalty of 9 percent that fades to zero after the first decade of a worker's career. The adjustment process is found to proceed over an increase in job mobility which is driven by improvements in firm characteristics. Moreover, they find that higher skilled graduates suffer less because they switch to better firms quickly while lower skilled entrants are permanently affected by bad entry conditions. Kahn (2006) focusses on white male college graduates in the US between 1979 and 1988. She uses the National Longitudinal Survey of Youth and finds even more persistent effects. The group graduating in the worst economic situation relative to those graduating in the best is found to suffer from a wage loss to up to 13% (or $80,000) each year over the first 20 years of a career. She further shows that those who graduate during recessions are more likely to go to graduate school and thus finds evidence for endogenous timing of labor market entry.[3] Both Kahn (2006) and Oreopoulos *et al.* (2006, 2008) tackle the endogeneity problem by instrumenting the business cycle indicator at the time of labor market entry with either the rate prevailing at a lower age or the rate in the year of predicted graduation. Other related studies are those from Oyer (2006a,b). However, like the previous two studies, he exclusively focuses on highly educated individuals. Looking at effects of Americans completing an MBA or a PhD in economics, respectively, during a recession he finds persistent negative effects for both groups. He shows that the cause of long-term effects on labor income of MBAs is the type of firm that employ them at a certain state of the economy (Oyer, 2006b). Looking at PhD economist he shows that people graduating in times when demand for economists is high are considerably more likely to get a position at a top 50 University (Oyer, 2006a). Thus, particularly among highly educated individuals where the transition in and out of attractive positions is very low, the first job evidently matters a great deal.[4]

Our study relies on a large and representative sample that consists of Austrian private-sector workers who start their first regular employment between 1978 and 2000 and whose wages are observable until 2005. The sample is drawn from the Austrian Social Security Database (ASSD), an exceptional rich data source with respect to both the coverage (along the cross-sectional as well as the longitudinal dimension) and the accuracy of information. Since the data are collected to calculate old-age benefits, they include very accurate information on

[3]There are several studies analyzing how schooling decision is affected by economic conditions. For example Oreopoulos *et al.* (2008) find the school duration to be endogenous and Gustman and Steinmeier (1981) and Bedard and Herman (2008) find that school enrollment rates appear to be counter-cyclical. In support of our focus on lower skilled workers, Bedard and Herman (2008) find that this appears to apply primarily to Masters and PhD enrollment decisions.

[4]Further related studies are from Raaum and Roed (2006) who show that individuals that face particularly depressed local labor market conditions when they finish school are at risk of higher adult unemployment. It is also shown that individuals who experience early job losses suffer from persistent earnings losses (Neumark, 2002; Ryan, 2001; von Wachter and Bender, 2006). Aslund and Rooth (2007) confirm long-run impacts of entry conditions by showing that a high unemployment rate at the time of immigration affect immigrant earnings for at least ten years.

annual earnings and daily employment and are thus perfectly suited for this kind of research question. The date of first entry into the labor force is conceptualized as the starting date of an individual's first regular employment spell. For each individual, we can keep track of his or her wage and employment status along with information about the employer for up to 27 years. Therefore we are able to observe job movements across firms, industries and regions. Unlike most other studies with a similar focus, we direct our attention to males at the lower half of the educational distribution and not on the highest skilled workers. The study by Burgess *et al.* (2003) shows that the effects of initial conditions are largest for lower skilled workers. Also, as on-the-job training and promotions are presumably less relevant in our sample, we can work out individuals' mobility behavior as a primary mechanism of adaptation to labor market shocks with more clarity than it is possible otherwise.

Our findings complement the existing literature in several important areas. First, we provide descriptive evidence on some key features of cohort-specific wage profiles for a large number of individuals and years. This allows us to present evidence on stylized facts of cohort-specific wage profiles. Second, our findings add new results on the small but growing literature that explores long term effects of labor market shocks, where – to the best of our knowledge – our study is the first to look at a European country. It also contributes to the internal labor market literature as our results support the stylized fact that entrant wages are more affected by cyclical economic fluctuations than incumbents' workers wages.[5] Third, because we have access to matched employer-employee data, we can not only track individuals' earnings and employment over the business cycle, but we can also track how workers move between firms, industries and regions. We thereby add evidence on wage-setting processes in the "real" labor market, as evidence on both the persistence of shocks and individuals' adjustment to such shocks over time are highly informative about these processes.

The remainder of this paper is organized as follows. In section 2 we begin by presenting the data source and discussing issues regarding the selection of the sample of labor market entrants and the construction of our key variables. The empirical analysis stretches over three consecutive sections. We start by describing the association between the (timing of) labor market entry and external labor market conditions in section 3, using both aggregate and individual-level data. We then proceed to the estimation of the immediate effects on starting wages in section 4. Section 5 presents some key features of cohort-specific wage profiles and our main results on the long–run effects on the subsequent wage profiles. In section 6 we study individuals' mobility patterns across firms, industries and regions. Section 7 sums up the key results and concludes.

[5]The internal labor literature argues with an implicit shielding agreement to which employers and workers agree within the wage determination process. Empirical studies like those from Baker *et al.* (1994) and Grant (2002) confirm this argument. Moreover, Beaudry and DiNardo (1991) find that the internal labor market augment incumbents' wages when the external labor market is tight while shielding their wages when it is slack.

2 Data and Sample

2.1 Data Sources

We mainly rely on data from the Austrian Social Security Database (ASSD), an exceptional source of data that essentially covers the universe of private sector workers in Austria (see Zweimüller *et al.*, 2008, for details). The ASSD contains virtually complete and very precise information about individuals' annual earnings and daily employment histories starting in January 1972 and running until December 2005. This data thus allows us to construct individual wage profiles for a huge number of labor market entrants over a relatively long period of time, implying that our data covers individuals belonging to different birth cohorts and, as we will show in section 2.4 below, both periods of boom and recession.

The ASSD contains very precise annual information about annual earnings, presumably without any significant amount of measurement error as this information is collected for the purpose of administering and calculating future old–age pension payments. However, annual pension contributions are right–censored because pension benefits are capped from above (i.e. there is a maximum pension benefit available), and thus the wage information in the ASSD is also right–censored. Similarly, there is a minimum level of earnings below which no social security contributions are accruing.[6] As we will show in section 2.2 below, the sample we choose effectively rules out the problem of censored wages. Our main dependent variable throughout the analysis is the real daily wage (i.e. the wage per day worked), which we compute by dividing annual earnings with the number of days worked in a given year, and then deflating using the consumer-price index ("Verbraucherpreisindex 1976") with base year 2007. The ASSD also contains several individual level characteristics which primarily relate to the job an individual holds like, for example, an individual is working as a blue-collar or a white-collar worker. However, one main drawback of the ASSD is that there is no exact information about schooling. We detail in section 2.2 and in appendix A on how we deal with this problem. Moreover, the data contain some important characteristics of the employer like, for example, the region and industry. More importantly still, the data allow tracking both individuals and firms over time, i.e. we have matched employer-employee data at our disposal. This will be important later on when we will look at mobility across firms, industries and regions (see section 6 below).

We use the official annual unemployment rate as our measure for external labor market conditions. The unemployment rate is available at the level of region×sex for the whole period of analysis (Bundeskammer für Arbeiter und Angestellte, 1980-2003). This rate covers all individuals in their working-age and it is the only rate available over the whole period of analysis.[7] However, the unemployment rate at an individuals' year of entry into the labor

[6] The two censoring points (in real terms) vary over time. The lower censoring point ("Mindestbeitragsgrundlage") has been increasing from about 14 € per workday in 1978 to about 26 € per workday in 2005. For the same two years, the real upper censoring point ("Höchstbemessungsgrundlage") has increased from about 78 € to 126 €.

[7] It is, in our view, not really obvious whether working with the youth unemployment rate would be preferable over working with the overall unemployment rate as the youth unemployment rate may potentially suffer from

market is observed at the group level only (i.e. the unemployment rate varies only across states and over years). We will have to take this fact into account later on when determining the precision of our estimates (e.g. Moulton, 1986, 1990).

2.2 Sample Selection

Our sample includes all men who fulfill the following two criteria. First, they have to enter the labor market between 1978 and 2000, such that we can potentially observe at least five years of earnings of each worker (remember that the data run until 2005). Second, we only consider workers who are aged between 15 and 21 years when they first enter the labor force.[8] This effectively is a restriction on individuals' duration of schooling, as we proxy schooling by the age at the start of one's first regular employment, and essentially excludes individuals with higher education (e.g. university degree) from the analysis but should include all or most individuals with an apprenticeship training or an education of similar length like full-time vocational school.[9]

We use this restriction on age at entry for three distinct reasons. First, and most importantly, the timing of entry into the labor market may be endogenous and so may the duration of schooling. One might easily imagine that individuals faced with a high unemployment rate might choose to postpone their entry into the labor force and to stay in school instead (and vice versa). We thus chose to include less skilled individuals because we think that they are less likely to manipulate the duration of schooling in order to counteract unfavorable entry conditions.[10] Second, unobserved heterogeneity resulting from, for example, unobserved differences in productivity presumably is a more urgent problem for highly-skilled workers than lower-skilled workers. Working with a sample of lower education thus helps dealing with unobserved heterogeneity. We will present some empirical evidence in favor of this argument below when discussing table 1. The third point relates to the fact that we have to use age at entry into the labor force as our proxy for education. Individuals who enter at a later age may belong to two very distinct but empirically not distinguishable groups of people. On the one hand, there are those really high-skilled workers who enter the labor market at a later stage because they have stayed in school until that time. On the other hand, however, there might also be those low-skilled workers who have been unemployed or only sporadically employed

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endogeneity bias. As Austria's youth unemployment rate is very low compared to most other countries (e.g. Breen, 2005), the choice between the two presumably is not that important.

[8] Remember that the ASSD covers the years 1972 until 2005. In order to determine the start of one's first job within the full range of 'education' in each year, we have to restrict the sample period to the years 1978–2000. In the year 1977, for example, we cannot determine the first entry into the labor market for an individual aged 21, because this individual might already have entered the labor market with age 15 (i.e. in the year 1971) - but this entry is not observable due the available observation period. Therefore, our focus on individuals within this age-bracket also allows for a larger observation period and more cohorts to be considered in the empirical analysis. Mention trade-off between the two dimensions.

[9] As we do not observe individuals' schooling, we work with the start of one' first regular employment spell instead (Gardecki and Neumark, 1998, do it the same way). See appendix A for more details.

[10] However, less skilled workers may be more likely to refrain from entering the labor force altogether. That's an important point and we will discuss its empirical content in detail in section 3.

before starting their first regular employment. Because schooling is not directly observed, we would mix these two groups of workers together. Again, we will provide some evidence in support of this argument below (see the discussion of table 1 below). Finally, as mentioned above, selecting less-skilled workers also minimizes the problem that wages are top-coded.

Table 1 shows some key variables by individuals' age when they first enter into the labor market, separately for men and women. Throughout, individuals who start their first regular employment after they turn 30 years old are not considered here as they presumably never enter the labor force at all.

Table 1

The first column in each section shows descriptives for all individuals, the second (third) column of each section shows descriptives for those individuals aged 15 to 21 (22 to 30) when entering the labor market. The comparison of the second and the third column of each section shows that our sample restriction works as expected, since the restriction on age at entry is essentially a restriction on educational attainment. With respect to men and women alike, our sample consists of more blue-collar workers with considerably lower wages and a shorter duration of their first employment spell than the group of higher skilled workers. Also note that in the group of individuals entering between 22 and 30, high-skilled workers are potentially mixed up with very low-skilled workers who start their first regular job only as they are quite old because they are unemployed or have only very short employment spells before. This is evident from the proportion of workers below the lower censoring point or above the higher censoring point, respectively. The probability of crossing any of the two points is higher for the sample of older workers.[11] Consequently, the variation in the real daily wage (and thus productivity) is considerably smaller in the sample of younger workers than in the group of older workers, regardless of the exact measure we look at. For example, the standard deviation of the log real daily wage is much higher in the group of older workers than in the group of younger workers.

As regards the location and the industry of a worker's first employment we see that we have more variation with respect to both of those variables in our sample than in the overall sample or the sample of older workers.

2.3 Sample Description

We start with describing the sample used in the subsequent analysis. Table 2 presents descriptive statistics which relate to the year of individuals' entry into the labor market for some key variables. That is, most of the variables shown in the table directly relate to the first regular employment spell (note that the first column reproduces (some of) the numbers from table 1). The first column of each section relates to the overall sample, the other two columns split the sample by the year they enter the labor market.

[11] This is consistent with the fact that a simple regression of the log real daily wage on age at entry (as proxy for schooling) both yields a higher point estimate and has a higher predictive value (as indicated by the R-Squared from the corresponding regression). This is true for men and women alike. These results are not shown but are available upon request.

Table 2

Probably the most important thing to notice is that there does not seem to be a huge change as regards the (distribution of) real starting wages, apart from an upward shift in the average real daily starting wage from about 43 € in the period 1978-1988 to about 52 € in the period 1989-2000. However, note that there is neither a marked change in the standard deviation nor in the probabilities of ending up in either tail of the starting wage distribution. This is good news for our empirical analysis, as this is evidence in favor of our strategy of sampling workers who are as similar as possible with respect to both observed and unobserved characteristics and at least the observed variables seem to be quite similar over time. The second important change over time is an increase in both the probability of experiencing any unemployment and the number of days spent in unemployment before actually entering the labor force. Therefore, age at entry into the labor force stays roughly constant over time although there is an increase in the age at start of one's first regular employment as this primarily reflects the increase in unemployment experience before entering the labor market. Again, this pattern emerges for both men and women alike.

Table 3 shows additional descriptive statistics that relate to the panel data.[12] The first column of each section (men and women, respectively) relates to the overall panel and the next two columns of each section split the panel by the number of potential years spent in the labor market (less than eight years in the second column and equal to or more than eight years in the third column of each section of the table).

Table 3

Panel A of table 3 shows descriptives for those variables that change over the years of potential labor market experience. The comparison with the corresponding figures from table 2 shows that there are significant changes over the time spent in the labor market.

More interestingly, panel B of table 3 shows descriptives for annual changes in log wages and changes in dummy variables indicating the employer and it's industry and geographical location at the level of the state (thus the changes in the dummies correspond to probabilities in mobility across firms, industries and regions). There are two key observations. First, increases in wages indeed happen at the beginning of individuals' labor market careers. Second, there is a related pattern in individuals' mobility, as the probability of changing employer, industry and region, respectively, is much higher in the earlier years of one's career than in the later years.

2.4 Fluctuations in Labor Market Conditions

The top panel of Figure 1 shows the business cycle in Austria over the years 1975 to 2000, measured as deviation in the logarithm of real GDP from its quadratic time trend. The bottom panel shows the deviation of the unemployment rate from a quadratic time trend. Clearly,

[12]Note that the figures in table 3 may also reflect sample attrition at some individuals may drop out temporarily or definitely from the labor market. We will take up this issue later in section 5.1.

our observation period covers both periods of boom and slack (compare with the dating of recessions given by Scheiblecker, 2002) and, as the comparison between the two figures shows, the overall unemployment rate closely tracks the time path of output growth.

Figure 1

Our key indicator for the state of the labor market however is the state- and year-specific unemployment rate. Figure 2 shows the fluctuation of the state-specific unemployment rates over time, for men and women separately. The Figure shows some striking differences between states with respect to both the level and the trend of the unemployment rate, revealing strong economic differences between states (see Hofer and Wörgötter, 1997).

Figure 2

The de-trended series for each state (bottom panel of Figure 2) focus on the cyclical pattern and show that the states are essentially faced with the same business cycle, i.e. the temporal pattern of boom and recession is basically the same. However, the extent of variation in the unemployment rate is quite different across states.

3 Labor Market Entry

The analysis of endogenous entry into the labor force, as well as the potential problem of endogenous duration of schooling, is complicated as we only observe individuals in our data once they have actually started to work. However, we can study the relation between the aggregate number of observed labor market entrants and the concurrent unemployment rate. Second, because we also observed days spent in unemployment we can check whether individuals are unemployed before they start their first regular job and thereby we can study the effect of the unemployment rate on the timing of entry into the labor force.

3.1 Participation

As discussed before, the selection of our analysis sample is primarily designed to minimize endogenous timing of labor market entry, i.e. individuals may choose to stay longer in school or may even refrain from entering the labor market altogether in a bad economic environment. In fact, non-participation may be a more severe problem than endogenous duration of schooling for our sample of less-skilled workers. Although we feel confident that such effects are quite small for our sample, we obviously can not rule out such effects on a priori grounds.

Figure 3

The primary driving force behind the number of actual labor market entrants, in our view, seems to be the size of the underlying cohorts. Figure 3 therefore shows the time path of the number of entrants, the unemployment rate, and the corresponding (approximate) cohort size (see appendix A on how these numbers were estimated). Figure 3 shows that the number of labor market entrants closely follows the trajectory of the cohort size and thus the number of potential labor market entrants, which itself primarily reflects the relative size of the baby boom (entering the labor market in the mid–eighties) and the subsequent birth cohorts. The unemployment rate, on the other hand, shows a clear upwards trend over the whole period, but no obvious relation to the number of labor market entrants.

Figure 4

Figure 4 digs somewhat deeper and shows the evolution of the number of entrants and the unemployment rate by sex and by state (the estimated cohort size is only available at the national level and is thus not shown in this figure). Note that the states differ widely with respect to both the level of the number of new entrants as well as the unemployment rate.

We also check econometrically whether there is evidence for endogenous labor market entry by correlating the number of new labor market entrants on the potential number of labor market entrants and on the contemporaneous unemployment rate:

$$\ln(\#e_{sjt}) = \alpha + \beta \ln(ur_{sjt}) + \gamma \ln(cs_{st}) + x_{sji}\delta + \epsilon_{sjt}, \tag{1}$$

where $\#e_{sjt}$ and ur_{sjt} correspond, respectively, to the absolute number of labor market entrants and the unemployment rate of sex s in state j and year t. The estimated cohort size of sex s in year t is given by cs_{st}, and x_{jt} denotes a vector of control variables including, for example, a female-dummy as men and women are pooled for the purpose of estimation. The parameter of main interest is β, the elasticity of the number of labor market entrants with respect to the unemployment rate. Results are shown in table 4.

Table 4

Not surprisingly, the estimated elasticity of the number of labor market entrants to the unemployment rate turns out to be negative throughout - the point estimate lies between about -0.17 to about -0.07. Note that an estimated elasticity within this range implies that the quantitative effect of changes in the unemployment rate on the number of entrants are surprisingly small - at least for males.[13]

3.2 Delayed Entry into the Labor Force

Next, we look at a the effect of the local unemployment rate on the timing of first entering the labor market. Because young workers are also eligible to unemployment benefits, we can

[13]The following "back of the envelope" calculation may illustrate this important point. On average, there are about 3,150 individuals entering the labor market per year and the unemployment rate is about 5.2 percentage points on average. Now, suppose there is an increase in the unemployment rate of one standard deviation, implying an increase in the unemployment rate from 5.2 to 7.2 percentage points (this would actually be a huge increase in the unemployment rate, as the average annual change is about 0.15 percentage points only). This corresponds roughly to a hypothetical increase in the log unemployment rate of about 0.4 (i.e. a relative increase of about 0.4). Multiplied with an estimate of the elasticity of -0.1 yields a predicted relative decrease in the number of entrants of about -0.04. This in turn would imply that, in absolute terms, about 125 individuals (per state) would refrain from entering the labor market (or enter at a later time) following quite a huge shock to the unemployment rate.

estimate the effect of the unemployment rate on the probability of experiencing any unemployment and the number of days spent in unemployment before one's first regular employment spell. We think that such estimates are informative about the timing of labor market entry. We therefore estimate models of the form:

$$ue_i^0 = \psi \left[\ln \left(ur_{j[i]}^0\right)\right] \cdot \alpha + x_i\beta + z_{j[i]}\gamma + \epsilon_i, \tag{2}$$

where ue_i^0 is the measure for unemployment experience before first regular employment (either a dummy variable indicating any unemployment or a variable counting the number of days unemployed before the start of one's first regular employment spell) of individual i, entering the labor market in state j. Function ψ denotes that we allow for higher-order polynomial terms of the initial unemployment rate. Control variables that are plausibly exogenous at the time of entry are included in vector x_i including. As has been shown in the preceding section, there have been marked changes in cohort size and the number of labor market entrants over time - vector z_{it} thus contains the logarithm of the number of labor market entrants and it's square term in order to control for these demographic shifts that may trigger corresponding changes in the unemployment rate per se.

Because the regressor of main interest, the unemployment rate at the time of first entering the labor market, $\ln(ur_{j[i]}^0)$, is a group-level regressor only - that is, because it varies at the state level only in a given year, some adjustment to the standard errors needs to be done as the unadjusted standard errors tend to grossly overstate statistical precision, even if state and year fixed effects are included as regressors (e.g. Moulton, 1986, 1990; Pepper, 2002). Thus, in all regressions shown, standard errors are adjusted for clustering at the state$\times$year level.

Tables 5

Table 5 shows our main results for men. The dependent variable in the first three columns is a dummy variable taking on the value one in case that an individual experiences any unemployment before he enters the labor market and zero otherwise; and it corresponds to the number of days unemployed before entering the labor market in the three remaining columns.

With respect to the individual probability of experiencing an unemployment spell before regular employment, there is a positive and statistically significant effect of the local unemployment rate at the year of entry - our preferred model (column three) yields an average elasticity of about 0.06. As in the case of aggregated data discussed before, the effect thus turns out to be quite small in economic terms.[14]

[14] Applying the same reasoning as in footnote 13 shows, for example, that a relative increase in the initial unemployment rate increases the male probability of experiencing any unemployment days before entering the labor market by less than three percentage points (i.e. $0.4 \cdot 0.063 = 0.025$). Also note that the confidence interval of the average elasticity given in column 3 of table 5 overlaps with the confidence interval of the elasticity of table 4 using aggregate data.

4 Immediate Effects: Starting Wages

The second part of our analysis focuses on the effect of the local unemployment rate at the time of entry into the labor market on starting wages (the empirical association between the unemployment rate and the wage is commonly referred to as the "wage curve" - note however that we focus on men newly entering the labor market only). We start by looking graphically at the association between the annual unemployment rate and the average starting wage over time. Because the two measures have very different time trends, figure 5 plots deviations from the respective time trend:[15]

Figure 5

Clearly, there is a quite strong negative association between the local unemployment rate on the one hand and the average starting wage on the other hand. The estimated elasticity of the starting wage to the concurrent unemployment rate is about -0.066.

To gain some more insight into this relation, Figure 6 plots the deviations of the unemployment rate and the starting wage from the time trend for each state separately.

Figure 6

Figure 6 underpins the negative correlation between the unemployment rate and the average starting wage. We can also see that this negative relation holds true for all states.

4.1 Econometric Analysis

To estimate the short–run effect of initial labor market conditions on individual starting wages we follow the literature and run regressions of the following form:[16]

$$\ln\left(y_{it}^0\right) = \psi\left[\ln\left(ur_{j[i]t}^0\right)\right] \cdot \alpha + x_{it}\beta + z_{j[i]}\gamma + \epsilon_{it}, \tag{3}$$

where y_i^0 is the starting wage of individual i, $ur_{j[i]}^0$ is the unemployment rate prevailing in the state j with which an individual i, entering the labor force in year t, is faced with. $\psi(\cdot)$ denotes that we use several polynomials of the initial unemployment rate. Vector x_{it} contains several individual characteristics (e.g. age at labor market entry, and variables indicating broad occupational groups), firm-specific characteristics (number of employees, region ("Bundesland") and industry of the firm), and a quadratic time trend to account for the fact that the workers enter the labor market at different years. $z_{j[i]}$ denotes the number of labor market entrants (in

[15]To be explicit, we estimate the following two equations for each state:

$$\begin{aligned}\widehat{\mathbb{E}[\ln(y_{it}^0)]} &= \hat{\lambda}_1 t + \hat{\lambda}_2 t^2, \quad \text{and} \\ \widehat{\ln(ur_t)} &= \hat{\delta}_1 t + \hat{\delta}_2 t^2,\end{aligned}$$

separately for men and women. We then plot $(\mathbb{E}[\ln(y_{it}^0)] - \widehat{\mathbb{E}[\ln(y_{it}^0)]})$ against $(\ln(ur_t) - \widehat{\ln(ur_t)})$.

[16]Note that, although we index with both i and t, the underlying data are not real panel data as we only observed one starting wage per individual. However, we also observe the longitudinal dimension as individuals enter in different years.

state j). Of main interest is parameter α, which corresponds to the elasticity of the starting wage with respect to the initial unemployment rate. As before, standard errors are clustered on the state×year level throughout.

Our main results with respect to the effect of the local unemployment rate on starting wages are shown in table 6.

Table 6

Results show that the association between the local unemployment rate and the average starting wage is indeed negative, whether we condition on potential confounding variables or not. As a matter of fact, conditioning on the set of controls does actually increase the estimate of α quite a bit (compare the first two columns to the remaining columns), suggesting that there are compositional changes at work. Only including a quadratic time trend yields an estimated elasticity of about -0.05 to about -0.06 (first two columns of table 6). Adding more control variables to the model increases the estimated elasticity to about -0.09 to about -0.13, depending on the selected group of controls and on the polynomial order used for modeling the effect of the unemployment rate. Overall, our results seem to be very well in line with the existing literature (e.g. Blanchflower and Oswald, 1990).

4.2 Robustness

The effect of the initial local unemployment rate on starting wages turns out to be surprisingly robust to a wide range of robustness checks. Table 7 shows some simple robustness checks with respect to either the selection of the sample or to model specification, and table 8 shows results for alternative outcome measures.[17]

Tables 7 and 8

Give some more details

4.3 Changes in the Distribution of Starting Wages

Now, the unemployment rate might not only have an effect on the mean of the distribution of starting wages, but also on the shape of the distribution. Specifically, one might reason that the effect on the individuals at the lower tail of the distribution might differ from the effect on those at the upper tail. Quantile regression is perfectly suited for investigating this issue (e.g. Angrist *et al.*, 2006).[18]

Table 9

[17]We also did some additional checks. For example, we checked the sensitivity with respect to age and year of entry into the labor force (results not shown). Again, we find a negative effect of the unemployment rate on the starting wage for every subsample.

[18]Somewhat surprisingly, no study has yet explored the relation between unemployment rate and moments of the starting wage distribution apart from the mean. However, this might simply be due to the fact that most studies have access to cell-level data only (as, for example, Oreopoulos *et al.*, 2006, 2008).

Table 9 therefore presents the results for different quantiles of the distribution of starting wages. The estimated elasticity is surprisingly similar across different quantiles (the only exception being the marginal effect on the first decile where the effect is quite a lot smaller). Overall, these estimates imply that an increase in the local unemployment rate at time of entry leads to a compression in the distribution of starting wages.

5 The Persistence of Labor Market Shocks

We now turn to the focal object of our empirical analysis, which is estimating the long-run effects of initial labor market conditions. Compared to the analysis of starting wages, things get a bit more complicated. A first issue is that standard panel-data methods (i.e. taking first differences or using fixed-effects estimation) that allow us to get rid of time-invariant unobserved heterogeneity also wipe away any time-variant regressors. This is obviously a problem for our analysis as our regressor of main interest does not vary over time. However, we are able to condition out a significant part of unobserved heterogeneity using a set of time-invariant variables like, for example, an individual's rank in the distribution of starting wages and the age when starting his or her first regular employment spell. However, the two aggregate level variables (initial unemployment rate and the number of labor market entrants) also explain a significant share of unobserved heterogeneity (appendix B provides additional details). Moreover, because there is collinearity between individuals' date of entry into the labor force, their age (i.e. calender time) and their labor market experience (e.g. Rodgers, 1982), it most often seems useful to restrict some of the involved parameters.

5.1 Some Key Features of Cohort-Specific Wage Profiles

To start with, we provide some figures of what we think are key features of cohort-specific wage profiles. As will become clear, some of these features are important later on for the econometric models. First, figure 7 shows how the cross-sectional wage distribution evolves over the number of years spent in the labor market.

Figure 7

There are two points worth making. First, the distribution of wages shifts considerably upwards as we move from unexperienced to more experienced workers. Moreover, not only does the average increase, but so does the spread in wages too.

To see more clearly how wages evolve over time, figure 8 plots cohort-specific wage profiles versus calendar time (note again that a cohort is defined by the year of labor market entry, not the year of birth).

Figures 8, 9 and 10

The black dots show the average log real daily starting wage of a given entry cohort and the dotted line correspondingly shows how the average log starting wage changes over time. The filled colored lines represent the wage profiles of the cohorts entering the labor market in different years. Clearly, cohorts' wages follow a concave path over time, which implies that wage growth is highest in the earlier years of an individual's labor market career. Figures 9 and 10 make the differences in wage profiles across cohorts more clear by re-scaling the data. Figure 9 rescales the abscissa, showing how wages evolve over years spent in the labor market instead of calender time. Figure 10 additionally rescales the ordinate by subtracting the corresponding log starting wage from each yearly average log wage (i.e. the ordinate of figure 10 therefore approximates the average wage growth).

Next, figure 11 shows how the standard deviation of log wages evolves over time and by entry cohort (a very similar qualitative pattern is found by Baker and Solon (2003)). As before, the dotted grey line shows the evolution of the variation in starting wages across different cohorts and the filled colored lines show the temporal path of the variation in wages for a given entry cohort.

Figure 11

The variation in wages decreases strongly in the first few years and then increases again after about four to six years of experience. The initial decrease in wage dispersion seems to fit the fact that individuals' mobility is highest in their early years in the labor market, as early job mobility is most often associated with an increase in the real wage rate (see figure 12 below). The subsequent increase probably reflects individuals' differential careers and occupational specialization within firms.

Figure 12 shows analogous profiles of cohort-specific job mobility (i.e. the vertical axis shows the probability of a change in employer between year t and year $t + 1$).

Figure 12

In contrast to wages, mobility profiles have a notable non-monotonic feature as the probability of switching employers first increases and then immediately reaches its peak in the second year of potential experience (i.e. the probability of moving between jobs is highest between the first and the second full year of labor market experience). Thereafter, it monotonically decreases with the time spent in the labor market, presumably because the quality of match between worker and job increases over time and/or that the costs of search and mobility increase as an individual ages.

Figure 13

Figure 13 shows the fraction of job changes associated with an increase in the real daily wage and, in contrast to most other features, there seems to exist a very pronounced cyclical component.

Next, we turn to the number of employment days in a given year. For men, there is a steep concave profile. This implies that the probability of getting unemployed decreases with the time spent in the labor market. However, it also seems conceivable that workers move to more stable employment as they age (consistent with the fact that the probability of changing job decreases as individuals are getting older).

Figures 14

Finally, we also show how the number of observations of a given cohort changes over time. As we track individuals over time as long as they have positive earnings, these figures essentially show participation patterns.

Figures 15

Participation patterns mirror the paths of the number of employment days.

5.2 Econometric Analysis

We estimate the long-run impact of the initial unemployment rate on wages by fitting regression models of the following form:

$$\ln(y_{it}) = \psi\left[\ln\left(ur^{0}_{j[i]t}\right), \exp_{it}\right] \cdot \alpha + x_{it}\beta + z_i\gamma + \epsilon_{it}, \tag{4}$$

where i and t index the individual and the calender year, respectively. The dependent variable y_{it} denotes the real daily wage of individual i in year t. The key regressor is again the initial local unemployment rate in state j, given by $ur^{0}_{j[i]}$. The number of potential years of the labor market experience of individual i are denoted by $\exp_{it}$. Function ψ again denotes that we allow for a flexible parametric form with respect to the initial unemployment rate and potential labor market experience (i.e. we also include the interaction terms between the two variables in some of the regression models that will be discussed below). Vector x_{it} represents a set of time-variant control variables. Finally, we also include several time-invariant regressors, represented by vector z_i, in order to minimize potential bias from unobserved heterogeneity (see also appendix B for details).

Serial correlation may be an additional issue (see Bertrand *et al.*, 2004; Donald and Lang, 2007). We therefore apply the multiway-clustering method proposed by Cameron *et al.* (2006). This method allows for clustering at the level of the year and at the level of the state at the same time. However, this adjustment may be overly conservative if there are only few clusters (Wooldridge, 2003).

The exposition of the key results - we are still primarily interested in the effect of the initial unemployment rate on the average wage profile - gets a little tricky because we allow this effect to vary with labor market experience. Therefore, we not only present point estimates for the key regressors, but we also provide the marginal effects of the initial unemployment rate at specific values of labor market experience (along with the corresponding robust standard errors). On top of that, we also show the whole wage profile as predicted by the underlying regression estimates for hypothetical individuals entering the labor market at a differing initial unemployment rate but otherwise identical on observable characteristics.[19]

Table 10 shows our main results. Based on our findings for the starting wages, we allow for a nonlinear effect of both labor market experience and the logarithm of the initial unemployment rate in all regressions.[20] All regressions include individual controls, a quadratic time trend, a full set of dummies in order to control for industry and state fixed effects, and controls for the number of labor market entrants.

Table 10, Figures 16 to 18

The first model restricts the effect of the initial unemployment rate to be constant over the number of labor market experience.[21] Still, there results a negative and statistically significant estimate of the elasticity of the initial unemployment rate to the wage of about -0.016 if evaluated at the mean of the initial unemployment rate. However, imposing a constant effect does not seem appropriate as we expect wages to adjust to initial shocks and thus the effect of the initial unemployment rate to depend on labor market experience. Therefore, the remaining models also include the interactions between the two polynomials of experience and the two polynomials of the log initial unemployment rate. Column 2 of table 10 adds these interaction terms and reveals an interesting pattern of the estimated elasticity of the wage to the initial unemployment rate. The immediate (marginal) impact of the initial unemployment rate is now larger than the constant effect from the first model. However, this negative effect has faded away after about five years of experience and only gets significantly negative again after about twenty years of experience.

One potential problem is that the overall sample is mechanically unbalanced, i.e. individuals entering the labor market in the earlier years of the analysis period are potentially observable for a longer period of time. Table 11 therefore replicates the final model from above (last column of table 10) based on different samples balanced with respect to potential labor market experience. For example, the first sample is made up of all individuals for whom we can potentially observe at least five years, and then only those observations within the first five years of tenure are kept in order to balance the sample in this respect.

Table 11, Figures 19 and 20

The results turn out to be robust to the choice of sample.

[19]More specifically, we compute:

$$\psi\left[\ln\left(ur_m^0\right), \exp\right] \cdot \widehat{\alpha} + \overline{x}\widehat{\beta} + \overline{z}\widehat{\gamma},$$

for each value of exp from 0 to an upper value $\overline{\exp}$, which itself is determined by the sample used for estimating the parameters, and for three different values of the logarithm of the initial unemployment rate (m being either the first decile, the mean, or the ninth decile of the distribution of $\ln(ur_m^0)$). This yields the predicted wage profile for an hypothetical individual with average characteristics entering the labor market at a different initial unemployment rate.

[20]We also estimated models where the initial unemployment rate only had a linear effect. The results are qualitatively the same (results not shown).

[21]To save space, we do not report full regression results. They are available upon request however.

5.3 Robustness

to be done

5.4 Disentangling the Effects of Initial and Current Unemployment

to be done

6 Adjustment to Shocks: Individuals' Mobility Patterns

As we focus on individuals with lower skills, explanations based on on-the-job training and promotions within firms are presumably less relevant than for the highly skilled workers. We therefore look at individuals' mobility patterns and see whether they match the findings from the preceding section. We have already seen some pieces of evidence in section 5.1 before.

6.1 Descriptive Analysis

to be done

6.2 Econometric Analysis

To pin down the effect of the initial unemployment rate on individuals' mobility, we estimate regression models that are basically equivalent to the wage regressions from the preceding section:

$$\mathbf{1}(\text{change}_{it}) = \psi \left[\ln \left(ur^{0}_{j[i]t} \right), \exp_{it} \right] \cdot \alpha + x_{it}\beta + z_i\gamma + \epsilon_{it}, \tag{5}$$

with the dependent variable now being an indicator function taking on the value one if individual i changes his or her employer, industry, or region between two consecutive years (i.e. between t and $t+1$), respectively. The right hand side of equation (5) corresponds to exactly the same specification as we have used before to estimate the effects of the initial unemployment rate on the wage rate.

Our key results are presented in table 12. Based on descriptive evidence on individuals' mobility patterns (see section 5.1 above), we estimate two different specifications for each outcome. For each outcome, the first specification includes all observations and the second only those observations for which labor market experience is equal to or greater than two years (i.e. this second specification excludes changes from the first to the second year in the labor market). We use this second specification because the descriptive evidence clearly shows a strong nonlinear pattern in individuals' mobility pattern.

Table 12, Figure 21

Table 12 makes it clear that in this case the choice of the specification is indeed crucial. Looking at the first specification, there does not seem to exist any effect of the initial unemployment rate on individuals' mobility across firms and regions. Figure 21, which shows the mobility pattern with changes between the first and the second year excluded, clearly shows that individuals facing a high initial unemployment rate are significantly more likely to change the employer in their first working years. In accordance with the predicted wage profiles, this effect fades away after five to six years of experience. This finding also coincides with the effect on the probability of changing the working region, however, this effect is more persistent. Interestingly, a higher initial unemployment rate leads to fewer industry changes at least during the first 10 years of experience.

7 Conclusions

We find some evidence on endogenous (timing of) labor market entry, however, these effects appear rather small what is consistent with the fact that Austria has a low youth unemployment rate. Thus, there probably are compositional effects. However, this would mean that our results, at least for the entry wages, even underestimate the true effects if we assume that the individuals who don't find a job are the less skilled and thus at the lower tail of the wage distribution. The analysis of wage effects of initial labor market conditions reveals robust evidence on negative short-run effects. Quantile regressions show that the effect is largest for higher wages. This means the wage distribution is compressed in times of high unemployment. This effect appears to be quite persistent, but fades away after about five to seven years of labor market experience. The mobility pattern coincides with the predicted catch-up effect in wages. We find the initially unluckier cohort to exhibit a higher probability to change the employer (and the region) during the first few years than the initially luckier cohort. Interestingly, this holds not true for the probability of changing the industry. There it is exactly the other way around.

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Table 1: Sample selection

	Men			Women		
Age at entry	15-30	15-21	22-30	15-30	15-21	22-30
Age at start of first job	20.760	19.097	24.386	19.908	18.380	24.353
	(3.010)	(1.160)	(2.589)	(3.132)	(1.403)	(2.463)
Blue collar	0.650	0.724	0.487	0.346	0.356	0.318
	(0.477)	(0.447)	(0.500)	(0.476)	(0.479)	(0.466)
Below GfGr	0.039	0.033	0.053	0.134	0.141	0.116
	(0.194)	(0.178)	(0.225)	(0.341)	(0.348)	(0.320)
Above HBGr	0.014	0.002	0.040	0.005	0.000	0.019
	(0.118)	(0.046)	(0.196)	(0.070)	(0.014)	(0.135)
Duration of first job	2.807	2.705	3.030	3.125	3.272	2.696
	(3.983)	(4.016)	(3.900)	(3.530)	(3.651)	(3.110)
Daily wage	34.805	31.774	41.411	26.478	23.450	35.290
	(16.142)	(13.639)	(18.957)	(14.007)	(10.934)	(17.746)
ln(daily wage)	3.441	3.361	3.614	3.139	3.039	3.431
	(0.486)	(0.462)	(0.493)	(0.542)	(0.504)	(0.542)
Real daily wage	50.106	47.062	56.742	38.465	35.206	47.948
	(18.747)	(15.491)	(23.027)	(16.792)	(12.979)	(22.168)
ln(real daily wage)	3.840	3.790	3.948	3.551	3.481	3.752
	(0.407)	(0.372)	(0.456)	(0.466)	(0.427)	(0.516)
White collar	0.348	0.273	0.510	0.644	0.635	0.672
	(0.476)	(0.446)	(0.500)	(0.479)	(0.481)	(0.470)
Region of employer						
Vienna	0.239	0.198	0.326	0.260	0.229	0.352
	(0.426)	(0.399)	(0.469)	(0.439)	(0.420)	(0.478)
Lower Austria	0.157	0.170	0.129	0.135	0.142	0.115
	(0.364)	(0.376)	(0.336)	(0.342)	(0.349)	(0.319)
Burgenland	0.024	0.025	0.021	0.021	0.023	0.018
	(0.152)	(0.156)	(0.142)	(0.145)	(0.149)	(0.133)
Upper Austria	0.169	0.184	0.137	0.168	0.183	0.123
	(0.375)	(0.388)	(0.344)	(0.374)	(0.387)	(0.328)
Styria	0.139	0.144	0.129	0.133	0.137	0.123
	(0.346)	(0.351)	(0.335)	(0.340)	(0.343)	(0.328)
Carinthia	0.064	0.065	0.062	0.065	0.064	0.065
	(0.245)	(0.247)	(0.241)	(0.246)	(0.245)	(0.247)
Salzburg	0.070	0.071	0.067	0.076	0.077	0.073
	(0.255)	(0.257)	(0.249)	(0.265)	(0.266)	(0.260)
Tyrol	0.090	0.092	0.087	0.095	0.096	0.091
	(0.287)	(0.289)	(0.282)	(0.293)	(0.295)	(0.288)
Vorarlberg	0.048	0.051	0.042	0.047	0.050	0.040
	(0.214)	(0.219)	(0.201)	(0.212)	(0.217)	(0.195)
Industry of employer						
Agriculture	0.015	0.012	0.021	0.009	0.010	0.008
	(0.121)	(0.110)	(0.142)	(0.095)	(0.097)	(0.089)
Electricity	0.007	0.009	0.003	0.002	0.002	0.001
	(0.084)	(0.094)	(0.057)	(0.044)	(0.048)	(0.032)
Mining	0.006	0.007	0.005	0.001	0.001	0.001
	(0.078)	(0.082)	(0.068)	(0.036)	(0.038)	(0.030)
Manufacturing	0.344	0.399	0.225	0.197	0.223	0.118
	(0.475)	(0.490)	(0.417)	(0.397)	(0.417)	(0.323)

Construction	0.164	0.188	0.114	0.020	0.022	0.013
	(0.371)	(0.390)	(0.318)	(0.139)	(0.146)	(0.114)
Wholesale and retail trade	0.149	0.157	0.130	0.214	0.240	0.138
	(0.356)	(0.364)	(0.336)	(0.410)	(0.427)	(0.345)
Gastronomy, hotel business	0.059	0.045	0.089	0.108	0.095	0.146
	(0.236)	(0.208)	(0.285)	(0.310)	(0.293)	(0.353)
Transportation	0.061	0.063	0.057	0.030	0.028	0.034
	(0.240)	(0.243)	(0.233)	(0.169)	(0.165)	(0.181)
Finance	0.081	0.058	0.130	0.102	0.101	0.105
	(0.273)	(0.235)	(0.337)	(0.302)	(0.301)	(0.307)
Cleaning, body care	0.009	0.008	0.012	0.047	0.051	0.037
	(0.096)	(0.089)	(0.109)	(0.212)	(0.220)	(0.188)
Arts, entertainment, sports	0.010	0.005	0.021	0.009	0.006	0.021
	(0.101)	(0.072)	(0.145)	(0.097)	(0.075)	(0.142)
Healthcare, welfare	0.014	0.007	0.029	0.072	0.071	0.075
	(0.116)	(0.081)	(0.167)	(0.259)	(0.258)	(0.263)
Education, research	0.015	0.005	0.037	0.059	0.047	0.091
	(0.121)	(0.070)	(0.189)	(0.235)	(0.212)	(0.288)
Lobbies, social security agencies	0.064	0.035	0.125	0.122	0.095	0.202
	(0.244)	(0.185)	(0.331)	(0.328)	(0.293)	(0.401)
Housekeeping	0.001	0.000	0.002	0.008	0.008	0.010
	(0.029)	(0.022)	(0.040)	(0.090)	(0.087)	(0.098)
n	1197704	821028	376676	1100491	819025	281466

Table 2: Summary statistics, by sex and year of entry

	Men			Women		
Year of entry	1978-2000	1978-1988	1989-2000	1978-2000	1978-1988	1989-2000
Age at start of first job	19.097	18.941	19.247	18.360	18.065	18.707
	(1.154)	(1.199)	(1.089)	(1.409)	(1.441)	(1.288)
Age at entry into labor force	18.574	18.797	18.359	17.920	17.984	17.846
	(1.527)	(1.162)	(1.783)	(1.581)	(1.405)	(1.762)
Duration of first regular job	2.853	3.133	2.582	3.344	3.580	3.067
	(4.317)	(5.168)	(3.276)	(3.761)	(4.200)	(3.146)
UE days before	41.984	19.529	63.568	45.585	15.546	80.836
	(100.403)	(54.719)	(126.260)	(113.808)	(58.551)	(147.741)
Any UE before: Yes = 1	0.302	0.191	0.409	0.270	0.127	0.438
	(0.459)	(0.393)	(0.492)	(0.444)	(0.333)	(0.496)
Size of firm (in 100s)	5.912	7.467	4.418	7.100	7.292	6.874
	(25.083)	(30.063)	(18.990)	(29.545)	(29.704)	(29.356)
Share female	0.246	0.247	0.245	0.684	0.690	0.676
	(0.221)	(0.219)	(0.223)	(0.269)	(0.268)	(0.269)
Blue collar	0.745	0.750	0.739	0.358	0.386	0.326
	(0.436)	(0.433)	(0.439)	(0.480)	(0.487)	(0.469)
White collar	0.253	0.247	0.258	0.634	0.602	0.671
	(0.435)	(0.431)	(0.438)	(0.482)	(0.489)	(0.470)
Real daily wage	47.834	43.485	52.014	35.191	32.180	38.724
	(15.572)	(14.117)	(15.759)	(12.872)	(11.324)	(13.656)
Nominal daily wage	33.054	24.825	40.964	23.763	18.170	30.326
	(13.965)	(8.844)	(13.403)	(11.063)	(6.939)	(11.390)
Below GfGr: Yes = 1	0.030	0.029	0.031	0.141	0.139	0.142
	(0.170)	(0.168)	(0.173)	(0.348)	(0.346)	(0.349)
Above HBGr: Yes = 1	0.002	0.002	0.002	0.000	0.000	0.000
	(0.046)	(0.047)	(0.046)	(0.012)	(0.013)	(0.011)
Number of quarters	3.941	3.947	3.935	3.904	3.903	3.904
	(0.340)	(0.323)	(0.356)	(0.451)	(0.452)	(0.450)
Region of employer						
Vienna	0.179	0.184	0.173	0.218	0.219	0.216
	(0.383)	(0.388)	(0.379)	(0.413)	(0.414)	(0.412)
Lower Austria	0.171	0.165	0.178	0.140	0.134	0.148
	(0.377)	(0.371)	(0.382)	(0.347)	(0.341)	(0.355)
Burgenland	0.025	0.023	0.026	0.022	0.024	0.021
	(0.156)	(0.151)	(0.160)	(0.148)	(0.152)	(0.142)
Upper Austria	0.195	0.194	0.195	0.189	0.192	0.186
	(0.396)	(0.395)	(0.397)	(0.392)	(0.394)	(0.389)
Styria	0.146	0.147	0.145	0.136	0.133	0.139
	(0.353)	(0.354)	(0.353)	(0.343)	(0.340)	(0.346)
Carinthia	0.066	0.071	0.062	0.066	0.070	0.061
	(0.249)	(0.257)	(0.240)	(0.248)	(0.255)	(0.239)
Salzburg	0.071	0.070	0.071	0.076	0.075	0.077
	(0.256)	(0.255)	(0.257)	(0.265)	(0.264)	(0.267)
Tyrol	0.093	0.093	0.093	0.099	0.100	0.099
	(0.291)	(0.290)	(0.291)	(0.299)	(0.300)	(0.298)
Vorarlberg	0.054	0.053	0.056	0.053	0.052	0.054
	(0.227)	(0.224)	(0.229)	(0.224)	(0.222)	(0.226)

Industry of employer						
Agriculture	0.011	0.012	0.010	0.009	0.008	0.010
	(0.102)	(0.107)	(0.098)	(0.095)	(0.089)	(0.101)
Electricity	0.010	0.010	0.009	0.002	0.003	0.002
	(0.099)	(0.101)	(0.096)	(0.049)	(0.052)	(0.044)
Mining	0.008	0.010	0.005	0.002	0.002	0.001
	(0.087)	(0.099)	(0.074)	(0.039)	(0.042)	(0.035)
Manufacturing	0.419	0.455	0.385	0.229	0.273	0.178
	(0.493)	(0.498)	(0.487)	(0.420)	(0.445)	(0.382)
Construction	0.200	0.198	0.202	0.023	0.021	0.024
	(0.400)	(0.399)	(0.402)	(0.149)	(0.145)	(0.153)
Wholesale and retail trade	0.158	0.146	0.169	0.246	0.241	0.253
	(0.364)	(0.353)	(0.375)	(0.431)	(0.427)	(0.435)
Gastronomy, hotel business	0.043	0.037	0.049	0.095	0.089	0.101
	(0.203)	(0.189)	(0.217)	(0.293)	(0.285)	(0.301)
Transportation	0.040	0.032	0.047	0.026	0.019	0.034
	(0.195)	(0.175)	(0.212)	(0.158)	(0.136)	(0.181)
Finance	0.059	0.050	0.069	0.102	0.089	0.117
	(0.236)	(0.217)	(0.253)	(0.302)	(0.284)	(0.321)
Cleaning, body care	0.008	0.007	0.008	0.050	0.044	0.058
	(0.088)	(0.083)	(0.092)	(0.219)	(0.205)	(0.233)
Arts, entertainment, sports	0.005	0.004	0.006	0.006	0.004	0.007
	(0.071)	(0.063)	(0.077)	(0.074)	(0.067)	(0.083)
Healthcare, welfare	0.007	0.005	0.009	0.074	0.067	0.082
	(0.084)	(0.074)	(0.093)	(0.262)	(0.250)	(0.275)
Education, research	0.005	0.004	0.006	0.046	0.047	0.043
	(0.071)	(0.065)	(0.077)	(0.209)	(0.213)	(0.204)
Lobbies, social security agencies	0.028	0.030	0.025	0.085	0.083	0.087
	(0.164)	(0.170)	(0.157)	(0.279)	(0.276)	(0.282)
Housekeeping	0.000	0.000	0.000	0.007	0.010	0.003
	(0.020)	(0.021)	(0.020)	(0.081)	(0.100)	(0.052)
n	223,900	109,733	114,167	262,167	141,548	120,619

Table 3: Summary statistics, panel data

	Men			Women		
Potential years of experience	0-27	1-7	8-27	0-27	0-7	8-27
A. Variables in levels						
Fraction of year employed	0.895	0.854	0.934	0.875	0.861	0.890
	(0.210)	(0.238)	(0.170)	(0.241)	(0.246)	(0.234)
Labor market experience	8.947	3.373	14.111	8.720	3.206	14.470
	(6.528)	(2.277)	(4.674)	(6.783)	(2.268)	(4.884)
Size of firm (in 100s)	6.496	6.280	6.697	10.347	9.083	11.665
	(23.623)	(24.466)	(22.811)	(33.836)	(32.805)	(34.830)
Share female	0.253	0.246	0.260	0.654	0.660	0.647
	(0.226)	(0.220)	(0.231)	(0.269)	(0.269)	(0.270)
Blue collar	0.644	0.690	0.602	0.306	0.323	0.287
	(0.479)	(0.463)	(0.490)	(0.461)	(0.468)	(0.453)
White collar	0.318	0.258	0.374	0.662	0.626	0.699
	(0.466)	(0.438)	(0.484)	(0.473)	(0.484)	(0.459)
Real daily wage	74.955	62.800	86.218	50.247	45.107	55.607
	(26.165)	(20.031)	(26.141)	(23.544)	(18.070)	(27.121)
ln(real daily wage)	4.250	4.083	4.405	3.792	3.710	3.878
	(0.386)	(0.357)	(0.344)	(0.547)	(0.494)	(0.585)
Nominal daily wage	61.329	47.331	74.299	40.441	33.357	47.829
	(26.111)	(19.247)	(24.910)	(21.915)	(16.355)	(24.399)
ln(nominal daily wage)	4.016	3.767	4.246	3.541	3.370	3.718
	(0.474)	(0.446)	(0.373)	(0.609)	(0.568)	(0.599)
Below GfGr: Yes = 1	0.012	0.016	0.008	0.103	0.096	0.110
	(0.107)	(0.124)	(0.089)	(0.304)	(0.295)	(0.313)
Above HBGr: Yes = 1	0.092	0.024	0.156	0.015	0.002	0.028
	(0.289)	(0.152)	(0.363)	(0.121)	(0.047)	(0.165)
number of quarters	3.954	3.955	3.954	3.934	3.938	3.931
	(0.290)	(0.289)	(0.291)	(0.364)	(0.354)	(0.375)
Region of employer						
Vienna	0.183	0.183	0.182	0.220	0.220	0.220
	(0.386)	(0.387)	(0.386)	(0.414)	(0.414)	(0.414)
Lower Austria	0.172	0.171	0.173	0.154	0.143	0.166
	(0.378)	(0.377)	(0.378)	(0.361)	(0.350)	(0.372)
Burgenland	0.022	0.023	0.022	0.025	0.022	0.027
	(0.148)	(0.149)	(0.148)	(0.155)	(0.147)	(0.162)
Upper Austria	0.198	0.198	0.198	0.189	0.191	0.187
	(0.399)	(0.399)	(0.399)	(0.391)	(0.393)	(0.390)
Styria	0.144	0.143	0.146	0.130	0.130	0.129
	(0.351)	(0.350)	(0.353)	(0.336)	(0.336)	(0.336)
Carinthia	0.066	0.065	0.068	0.066	0.064	0.068
	(0.248)	(0.246)	(0.251)	(0.248)	(0.245)	(0.251)
Salzburg	0.071	0.071	0.071	0.074	0.076	0.071
	(0.257)	(0.258)	(0.257)	(0.261)	(0.265)	(0.258)
Tyrol	0.093	0.094	0.093	0.095	0.101	0.088
	(0.291)	(0.292)	(0.290)	(0.293)	(0.301)	(0.284)
Vorarlberg	0.050	0.053	0.047	0.049	0.053	0.044
	(0.217)	(0.223)	(0.212)	(0.215)	(0.224)	(0.206)

Industry of employer						
Agriculture	0.009	0.009	0.008	0.007	0.008	0.006
	(0.093)	(0.095)	(0.090)	(0.083)	(0.087)	(0.079)
Electricity	0.014	0.011	0.017	0.003	0.003	0.004
	(0.119)	(0.104)	(0.130)	(0.058)	(0.054)	(0.062)
Mining	0.011	0.010	0.012	0.002	0.002	0.002
	(0.104)	(0.097)	(0.110)	(0.042)	(0.041)	(0.043)
Manufacturing	0.375	0.394	0.357	0.199	0.222	0.174
	(0.484)	(0.489)	(0.479)	(0.399)	(0.416)	(0.379)
Construction	0.165	0.181	0.150	0.025	0.023	0.026
	(0.371)	(0.385)	(0.357)	(0.155)	(0.149)	(0.160)
Wholesale and retail trade	0.157	0.159	0.155	0.232	0.236	0.228
	(0.364)	(0.366)	(0.362)	(0.422)	(0.425)	(0.419)
Gastronomy, hotel business	0.032	0.039	0.025	0.075	0.086	0.063
	(0.175)	(0.193)	(0.157)	(0.263)	(0.280)	(0.243)
Transportation	0.066	0.058	0.074	0.032	0.030	0.034
	(0.249)	(0.234)	(0.262)	(0.176)	(0.171)	(0.181)
Finance	0.082	0.073	0.090	0.117	0.112	0.123
	(0.274)	(0.260)	(0.286)	(0.321)	(0.315)	(0.328)
Cleaning, body care	0.007	0.007	0.006	0.036	0.043	0.028
	(0.081)	(0.084)	(0.079)	(0.185)	(0.202)	(0.166)
Arts, entertainment, sports	0.007	0.006	0.008	0.008	0.007	0.009
	(0.084)	(0.079)	(0.088)	(0.087)	(0.081)	(0.093)
Healthcare, welfare	0.014	0.010	0.018	0.095	0.083	0.107
	(0.119)	(0.100)	(0.134)	(0.293)	(0.275)	(0.310)
Education, research	0.005	0.005	0.006	0.024	0.032	0.015
	(0.072)	(0.068)	(0.075)	(0.152)	(0.176)	(0.120)
Lobbies, social security agencies	0.055	0.037	0.071	0.141	0.110	0.173
	(0.228)	(0.189)	(0.257)	(0.348)	(0.312)	(0.378)
Housekeeping	0.001	0.000	0.001	0.007	0.006	0.008
	(0.027)	(0.020)	(0.031)	(0.081)	(0.074)	(0.088)
n	3455895	1662082	1793813	3472824	1772871	1699953
B. Changes between two consecutive years						
Δ ln(real daily wage)	0.040	0.069	0.017	0.015	0.039	-0.008
	(0.197)	(0.218)	(0.175)	(0.377)	(0.385)	(0.368)
Δ ln(nominal daily wage)	0.063	0.095	0.038	0.039	0.067	0.013
	(0.198)	(0.219)	(0.175)	(0.377)	(0.386)	(0.368)
Δ ln(nominal daily wage) < 0	0.211	0.194	0.225	0.223	0.200	0.244
	(0.408)	(0.395)	(0.418)	(0.416)	(0.400)	(0.430)
Change of employer	0.191	0.237	0.153	0.178	0.221	0.136
	(0.393)	(0.425)	(0.360)	(0.382)	(0.415)	(0.343)
Change of industry	0.102	0.131	0.078	0.099	0.126	0.074
	(0.303)	(0.338)	(0.269)	(0.299)	(0.332)	(0.261)
Change of region	0.036	0.045	0.030	0.026	0.037	0.016
	(0.187)	(0.207)	(0.170)	(0.159)	(0.188)	(0.125)
n	3175396	1415580	1759816	2993355	1451596	1541759

Table 4: Number of labor market entrants

	ln_entry_15to21	ln_entry_15to21	ln_entry_15to21	ln_entry_15to21	ln_entry_15to21	ln_entry_15to21	ln_entry_22to30
ln_alq	−0.168***	−0.087***	−0.073***		−0.128***	−0.088***	−0.172***
	(0.059)	(0.018)	(0.023)		(0.024)	(0.025)	(0.052)
frau			7.364**	11.628***	5.962	9.444**	−9.726
			(3.700)	(3.467)	(4.255)	(3.851)	(8.125)
frauXln_alq			−0.086***		−0.105***	−0.050	−0.008
			(0.030)		(0.032)	(0.032)	(0.067)
ln_csize			1.646***	1.735***	1.821***	1.856***	2.986***
			(0.221)	(0.202)	(0.265)	(0.229)	(0.484)
frauXln_csize			−0.591*	−0.970***	−0.466	−0.774**	0.874
			(0.326)	(0.305)	(0.372)	(0.339)	(0.715)
jahr			0.047***	0.057***	0.060***	0.053***	0.367***
			(0.007)	(0.006)	(0.010)	(0.007)	(0.015)
jahrsq			−0.001***	−0.001***	−0.001***	−0.001***	−0.010***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
frauXjahr			−0.021**	−0.021***	−0.014	−0.030***	−0.031*
			(0.008)	(0.007)	(0.012)	(0.009)	(0.018)
frauXjahrsq			−0.000	−0.001**	−0.001*	−0.000	0.002***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
alq				−0.042***			
				(0.006)			
frauXalq				−0.023***			
				(0.007)			
Constant	8.110***	8.754***	−10.303***	−11.273***	−12.281***	−12.708***	−27.312***
	(0.097)	(0.038)	(2.528)	(2.307)	(3.040)	(2.622)	(5.531)
State dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Mean	7.853				7.852	8.025	7.089
Standard deviation	0.687				0.690	0.508	0.931
n	414	414	414	414	378	368	368
p (F–statistic)	0.005	0.000	0.000	0.000	0.000	0.000	0.000
R–squared	0.019	0.935	0.976	0.979	0.981	0.958	0.945
Adj. R–squared	0.017	0.934	0.975	0.978	0.980	0.957	0.942

Notes:

Table 5: Unemployment before first regular job, main results (men)

	anyue_before	anyue_before	anyue_before	uedur_before	uedur_before	uedur_before
Mean	0.302	0.302	0.302	41.984	41.984	41.984
Standard deviation	0.459	0.459	0.459	100.403	100.403	100.403
ln_alq0	0.043***	0.027***	−0.002	6.661***	4.594**	−5.489**
	(0.009)	(0.009)	(0.008)	(2.366)	(2.328)	(2.286)
ln_alq0_sq			0.022***			7.792***
			(0.004)			(1.126)
age at start of first regular job (years)		0.062***	0.062***		8.795***	8.796***
		(0.003)	(0.003)		(0.566)	(0.566)
blue-collar worker		0.014	0.013		2.584	2.469
		(0.022)	(0.022)		(4.771)	(4.742)
white-collar worker		−0.136***	−0.136***		−25.946***	−26.051***
		(0.022)	(0.022)		(4.766)	(4.749)
Constant	1.718	−0.371	−0.996	438.772	149.435	−67.096
	(1.099)	(1.075)	(1.100)	(293.419)	(286.769)	(285.995)
Quadratic time trend	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	Yes	Yes	No	Yes	Yes
Number of entrants	Yes	Yes	Yes	Yes	Yes	Yes
n	223, 900	223, 900	223, 900	223, 900	223, 900	223, 900
k	13	30	31	13	30	31
Adjusted R-Squared	0.089	0.137	0.137	0.075	0.102	0.103
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000
mfx			0.063			17.080
			(0.010)			(2.612)

Notes: Standard errors are in parentheses and are clustered on state-year cells.

Table 6: Starting wages, main results (men)

	ln_rdailywage	ln_rdailywage	ln_rdailywage	ln_rdailywage	ln_rdailywage	ln_rdailywage
Mean	3.808	3.808	3.808	3.808	3.808	3.808
Standard deviation	0.369	0.369	0.369	0.369	0.369	0.369
ln_alq0	−0.056***	−0.043***	−0.089***	−0.071***	−0.071***	−0.063***
	(0.007)	(0.010)	(0.009)	(0.008)	(0.009)	(0.007)
ln_alq0_sq		−0.007		−0.013***	−0.014***	−0.022***
		(0.004)		(0.004)	(0.004)	(0.003)
age at start of first regular job (years)			0.123***	0.123***	0.121***	0.121***
			(0.002)	(0.002)	(0.002)	(0.002)
blue-collar worker			0.447***	0.447***	0.460***	0.460***
			(0.064)	(0.064)	(0.063)	(0.063)
white-collar worker			0.388***	0.388***	0.410***	0.410***
			(0.065)	(0.065)	(0.064)	(0.064)
firmsize (in 100s)					0.001***	0.001***
					(0.000)	(0.000)
female share of workforce					−0.124***	−0.123***
					(0.006)	(0.006)
number of quarters firmsize observed					0.024***	0.024***
					(0.004)	(0.004)
Constant	3.643***	3.640***	0.771***	0.770***	0.725***	1.929*
	(0.010)	(0.010)	(0.069)	(0.069)	(0.072)	(1.096)
Quadratic time trend	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	No	No	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	Yes	Yes	Yes
Number of entrants	No	No	No	No	No	Yes
n	223,900	223,900	223,900	223,900	223,900	223,900
k	3	4	28	29	32	34
Adjusted R-Squared	0.074	0.074	0.295	0.295	0.303	0.304
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000
mfx		−0.062		−0.109	−0.111	−0.128
		(0.008)		(0.010)	(0.010)	(0.009)

Notes: Standard errors (in parentheses) are clustered on state-year cells.

Table 7: Starting wages, sensitivity checks (men)

	Yearly dummies	Year $\geq$ 1980	Wage $\geq$ GfGr	BL!=Burgenland	BC=1	WC=1	3. Polynomial
Mean	3.808	3.819	3.843	3.810	3.823	3.767	3.808
Standard deviation	0.369	0.366	0.305	0.369	0.350	0.394	0.369
ln_alq0	-0.038^{***}	-0.076^{***}	-0.060^{***}	-0.065^{***}	-0.058^{***}	-0.066^{***}	-0.063^{***}
	(0.009)	(0.009)	(0.006)	(0.008)	(0.008)	(0.010)	(0.008)
ln_alq0_sq	-0.018^{***}	-0.020^{***}	-0.019^{***}	-0.022^{***}	-0.023^{***}	-0.020^{***}	-0.023^{***}
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)
ln_alq0_cub							0.001
							(0.003)
age at start of first regular job	0.121^{***}	0.121^{***}	0.101^{***}	0.121^{***}	0.108^{***}	0.145^{***}	0.121^{***}
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
blue-collar worker	0.458^{***}	0.414^{***}	-0.148^{***}	0.452^{***}			0.460^{***}
	(0.063)	(0.061)	(0.020)	(0.062)			(0.063)
white-collar worker	0.408^{***}	0.364^{***}	-0.191^{***}	0.402^{***}			0.410^{***}
	(0.064)	(0.062)	(0.020)	(0.064)			(0.064)
firmsize (in 100s)	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.002^{***}	0.000^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
female share of workforce	-0.123^{***}	-0.130^{***}	-0.097^{***}	-0.126^{***}	-0.092^{***}	-0.158^{***}	-0.123^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)	(0.006)
number of quarters	0.023^{***}	0.025^{***}	-0.002	0.024^{***}	0.019^{***}	0.029^{***}	0.024^{***}
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)	(0.004)
Constant	2.074^{**}	1.698^{*}	2.351^{**}	1.385	2.330^{**}	2.693^{*}	1.944^{*}
	(0.872)	(1.009)	(1.019)	(1.246)	(1.125)	(1.453)	(1.091)
Quadratic time trend	No	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	No	No	No	No	No	No
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of entrants	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	223,900	207,177	217,213	218,321	166,708	56,602	223,900
k	54	34	34	33	32	32	35
Adjusted R-Squared	0.306	0.302	0.305	0.303	0.282	0.378	0.304
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
mfx	-0.091	-0.138	-0.115	-0.129	-0.126	-0.123	-0.131
	(0.011)	(0.010)	(0.008)	(0.010)	(0.010)	(0.012)	(0.022)

Notes: Standard errors (in parentheses) are clustered on state-year cells.

Table 8: Starting wages, alternative outcomes (men)

	ln_duration	ln_rannualwage	below GfGr: Yes = 1	aboveHBGr
Mean	5.377	9.184	0.030	0.002
Standard deviation	0.613	0.680	0.170	0.046
ln_alq0	0.043***	−0.020*	0.005*	−0.001
	(0.010)	(0.012)	(0.003)	(0.001)
ln_alq0_sq	−0.008	−0.030***	0.003**	−0.000
	(0.005)	(0.006)	(0.001)	(0.000)
age at start of first regular job (years)	−0.055***	0.066***	−0.025***	0.001***
	(0.003)	(0.003)	(0.001)	(0.000)
blue-collar worker	−0.020	0.440***	−0.256***	−0.009
	(0.031)	(0.065)	(0.024)	(0.006)
white-collar worker	0.005	0.415***	−0.247***	−0.009
	(0.032)	(0.067)	(0.024)	(0.006)
firmsize (in 100s)	−0.000***	0.001***	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
female share of workforce	−0.318***	−0.441***	0.028***	−0.004***
	(0.008)	(0.009)	(0.003)	(0.000)
number of quarters firmsize observed	0.210***	0.233***	−0.025***	−0.001**
	(0.006)	(0.006)	(0.002)	(0.000)
Constant	4.042**	5.971***	0.432	−0.004
	(1.702)	(1.602)	(0.329)	(0.072)
Quadratic time trend	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Number of entrants	Yes	Yes	Yes	Yes
n	223,900	223,900	223,900	223,900
k	34	34	34	34
Adjusted R-Squared	0.079	0.156	0.129	0.005
p-value (F-statistic)	0.000	0.000	0.000	0.000
mfx	0.020	−0.108	0.013	−0.002
	(0.014)	(0.015)	(0.003)	(0.001)

Notes: Standard errors (in parentheses) are clustered on state-year cells.

Table 9: Starting wages, quantile regressions (men)

	ln_rdailywage	ln_rdailywage	ln_rdailywage	ln_rdailywage	ln_rdailywage
ln_alq0	−0.031***	−0.056***	−0.067***	−0.066***	−0.066***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)
ln_alq0_sq	−0.025***	−0.020***	−0.020***	−0.020***	−0.018***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
age at start of first regular job (years)	0.170***	0.151***	0.107***	0.094***	0.091***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
blue-collar worker	1.720***	0.517***	0.019	−0.082***	−0.151***
	(0.023)	(0.018)	(0.014)	(0.014)	(0.019)
white-collar worker	1.676***	0.452***	−0.027**	−0.116***	−0.194***
	(0.023)	(0.018)	(0.014)	(0.014)	(0.019)
firmsize (in 100s)	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
female share of workforce	−0.068***	−0.060***	−0.131***	−0.162***	−0.202***
	(0.006)	(0.005)	(0.004)	(0.003)	(0.005)
number of quarters firmsize observed	0.060***	0.016***	0.010***	0.002	−0.010***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Constant	1.039	1.242**	1.273***	2.632***	3.144***
	(0.692)	(0.559)	(0.439)	(0.419)	(0.579)
Quadratic time trend	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Number of entrants	Yes	Yes	Yes	Yes	Yes
mean (dep. var.)					
s.d. (dep.var.)					
n	223, 900	223, 900	223, 900	223, 900	223, 900
Pseudo R^2	0.226	0.209	0.184	0.164	0.148
Quantile	0.10	0.25	0.50	0.75	0.90
mfx	−0.103	−0.115	−0.125	−0.124	−0.119
mfx_se	0.006	0.005	0.004	0.004	0.005

Notes:

Table 10: Wage profiles, main results (men)

	ln_rdwage	ln_rdwage	ln_rdwage	ln_rdwage	ln_rdwage	ln_rdwage
Mean	4.250	4.250	4.250	4.250	4.250	4.250
Standard deviation	0.386	0.386	0.386	0.386	0.386	0.386
ln_alq0	−0.003	−0.035**	−0.036***	−0.031**	−0.040**	−0.052***
	(0.006)	(0.016)	(0.014)	(0.014)	(0.018)	(0.018)
ln_alq0_sq	−0.005	−0.003	−0.009*	−0.007***	−0.006	−0.005
	(0.004)	(0.008)	(0.005)	(0.002)	(0.006)	(0.004)
expXln_alq0		0.007***	0.009***	0.009***	0.011***	0.012***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
expsqXln_alq0		−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
expXln_alq0_sq		0.001	0.002***	0.002***	0.001	0.001
		(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
expsqXln_alq0_sq		−0.000**	−0.000***	−0.000***	−0.000**	−0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Current unemployment	No	No	Yes	Yes	Yes	No
Entry vars	No	No	No	Yes	Yes	Yes
Interactions	No	No	No	No	Yes	Yes
n	3455895	3455895	3455895	3455895	3455895	3455895
k	36	40	43	68	120	117
Adjusted R-Squared	0.427	0.427	0.428	0.481	0.523	0.522
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000
mfx(0)	−0.016	−0.043	−0.061	−0.050	−0.056	−0.066
	(0.008)	(0.022)	(0.015)	(0.014)	(0.013)	(0.013)
mfx(5)		−0.007	−0.008	0.000	0.001	−0.005
		(0.012)	(0.009)	(0.008)	(0.007)	(0.008)
mfx(10)		0.004	0.013	0.021	0.025	0.022
		(0.008)	(0.007)	(0.006)	(0.005)	(0.006)
mfx(15)		−0.009	0.002	0.011	0.016	0.015
		(0.007)	(0.007)	(0.006)	(0.004)	(0.005)
mfx(20)		−0.047	−0.042	−0.028	−0.026	−0.026
		(0.010)	(0.011)	(0.010)	(0.009)	(0.009)

Notes: Robust standard errors (clustered on both state and year) are given in parentheses.

Table 11: Wage profiles, by experience/cohort (men)

	ln_rdwage	ln_rdwage	ln_rdwage	ln_rdwage
ln_alq0	−0.053**	−0.061**	−0.046***	−0.016*
	(0.022)	(0.024)	(0.014)	(0.009)
ln_alq0_sq	−0.002	−0.002	−0.009**	0.001
	(0.007)	(0.008)	(0.005)	(0.004)
expXln_alq0	0.008	0.021***	0.014***	0.009***
	(0.010)	(0.008)	(0.003)	(0.002)
expsqXln_alq0	0.001	−0.001**	−0.001***	−0.000***
	(0.002)	(0.001)	(0.000)	(0.000)
expXln_alq0_sq	−0.002**	0.001	0.004***	0.002***
	(0.001)	(0.003)	(0.001)	(0.000)
expsqXln_alq0_sq	−0.000	−0.000	−0.000***	−0.000***
	.	(0.000)	(0.000)	(0.000)
Individual vars	Yes	Yes	Yes	Yes
Quadratic time trend	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Number of entrants	Yes	Yes	Yes	Yes
Entry vars	Yes	Yes	Yes	Yes
Interactions	Yes	Yes	Yes	Yes
Mean	4.035	4.131	4.195	4.231
Standard deviation	0.355	0.363	0.379	0.394
n	1282418	1818218	1929716	1475042
k	117	117	117	117
Adjusted R-Squared	0.566	0.534	0.542	0.560
p-value (F-statistic)	0.000	0.000	0.000	0.000
mfx(0)	−0.058	−0.066	−0.069	−0.014
	(0.015)	(0.014)	(0.012)	(0.014)
mfx(5)	−0.009	0.010	0.015	0.030
	(0.011)	(0.005)	(0.008)	(0.009)
mfx(10)		0.014	0.034	0.042
		(0.006)	(0.006)	(0.007)
mfx(15)			−0.010	0.022
			(0.009)	(0.006)
mfx(20)				−0.030
				(0.013)

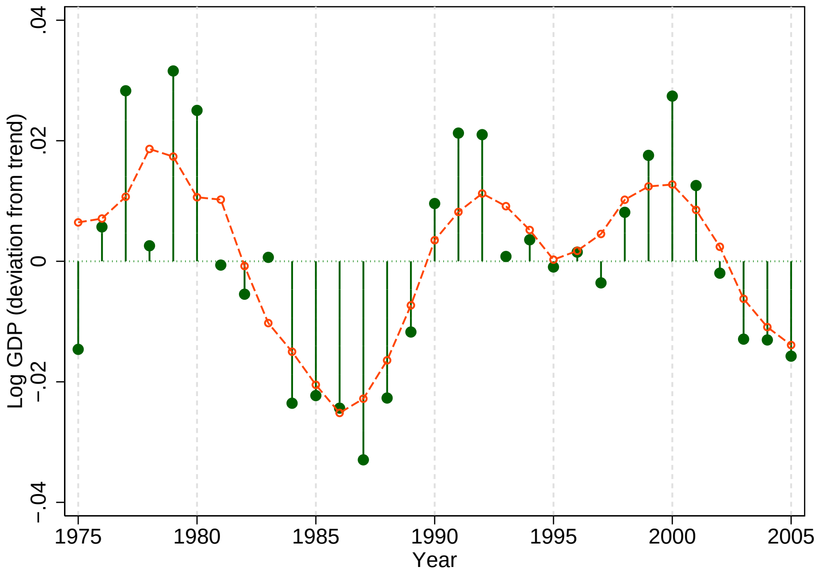
Notes: Robust standard errors (clustered on both state and year) are given in parentheses. ***, **, and * denote statistical significance on the 1%, 5%, and 10% level, respectively.

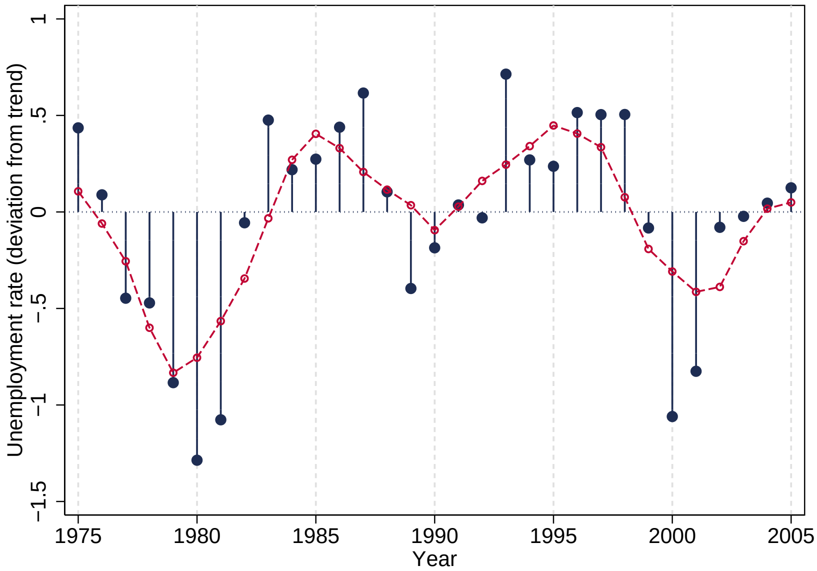
Table 12: Mobility profiles, main results (men)

	F.Jchange	F.Jchange	F.Ichange	F.Ichange	F.Rchange	F.Rchange
Mean	0.191	0.181	0.102	0.096	0.036	0.035
Standard deviation	0.393	0.385	0.303	0.295	0.187	0.185
ln_alq0	−0.010	0.005	−0.011**	−0.001	−0.003	−0.001
	(0.010)	(0.009)	(0.005)	(0.004)	(0.004)	(0.006)
ln_alq0_sq	0.002	0.006**	−0.000	0.002	0.002	0.008
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)
expXln_alq0	0.001	−0.002	0.001	−0.001	0.001*	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
expsqXln_alq0	−0.000	0.000	−0.000	0.000	−0.000	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	.	(0.000)
expXln_alq0_sq	0.000	−0.001**	0.000	−0.001	−0.000	−0.001*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
expsqXln_alq0_sq	−0.000	0.000***	−0.000	0.000**	−0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
n	3175396	2744006	3175396	2744006	3175396	2744006
k	117	117	117	117	117	117
Adjusted R-Squared	0.047	0.048	0.031	0.031	0.026	0.027
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000
mfx(0)	−0.005	0.021	−0.012	0.003	0.003	0.018
	(0.009)	(0.009)	(0.005)	(0.005)	(0.010)	(0.011)
mfx(5)	0.000	0.004	−0.006	−0.004	0.005	0.009
	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
mfx(10)	0.002	−0.004	−0.003	−0.006	0.004	0.002
	(0.003)	(.)	(0.002)	(0.001)	(.)	(.)
mfx(15)	−0.000	−0.004	−0.003	−0.004	−0.000	−0.002
	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
mfx(20)	−0.006	0.005	−0.005	0.003	−0.007	−0.004
	(0.009)	(0.006)	(0.004)	(0.003)	(0.006)	(0.005)

Notes: Robust standard errors (clustered on both state and year) are given in parentheses. All regressions include a full set of control variables.

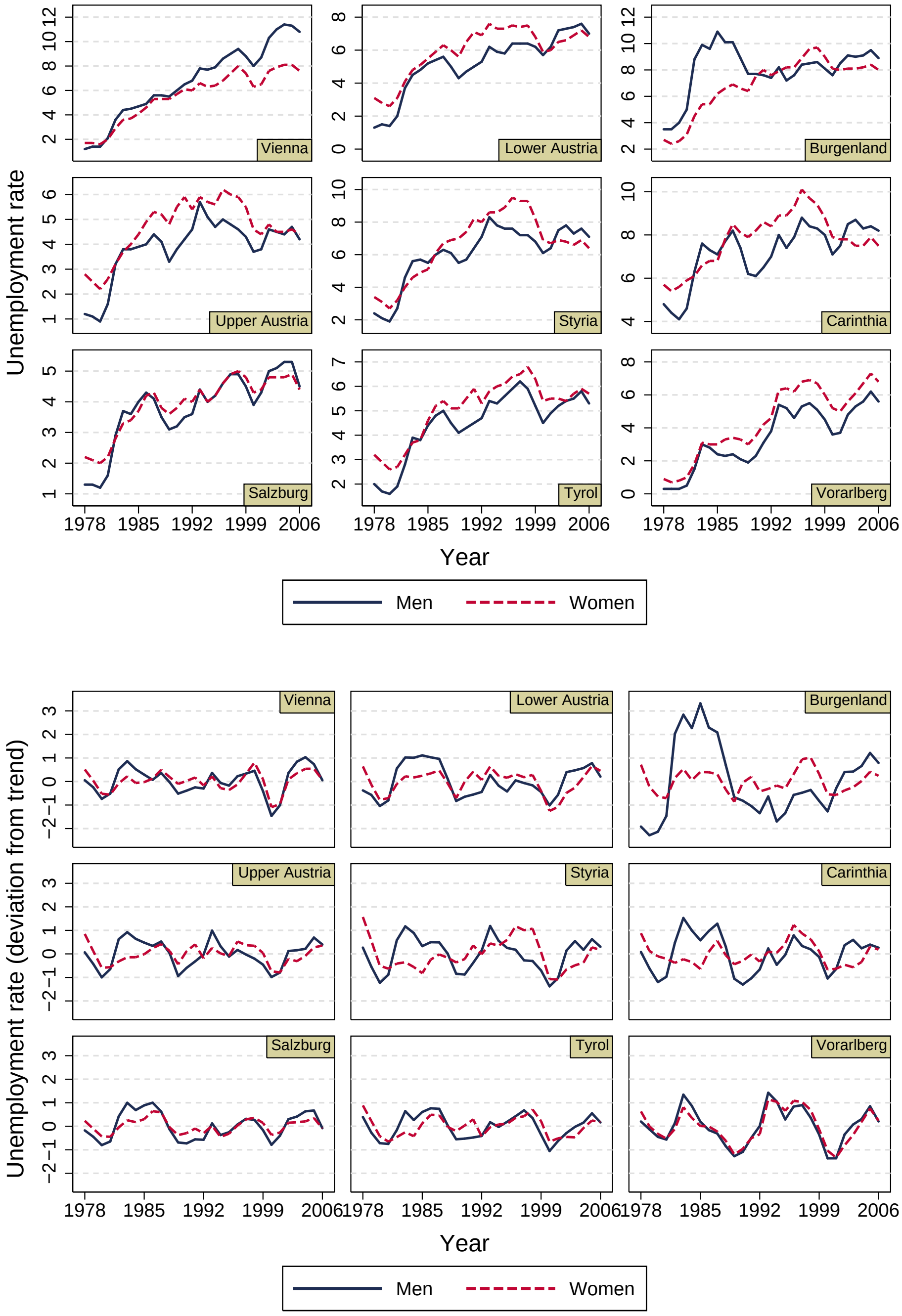
Figure 1: Business cylce in Austria, 1975–2005





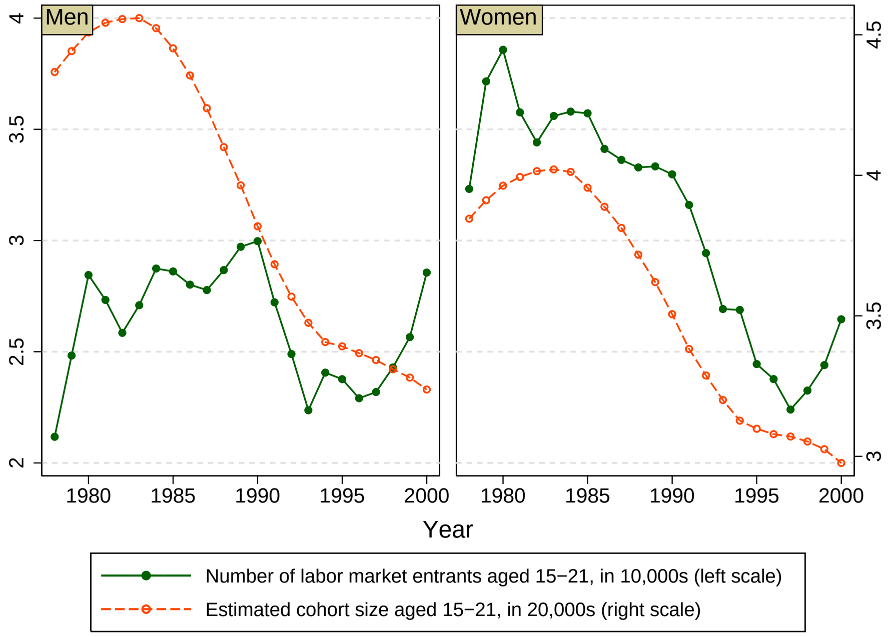
Notes: The figure at the top shows the deviation of the natural logarithm of real gross domestic product from a simple quadratic time trend. The solid line is the corresponding five-year moving average. The figure at the bottom shows the deviation of the unemployment rate (percentage points) from a simple quadratic time trend.
Sources: Statistik Austria, Bundeskammer für Arbeiter und Angestellte.

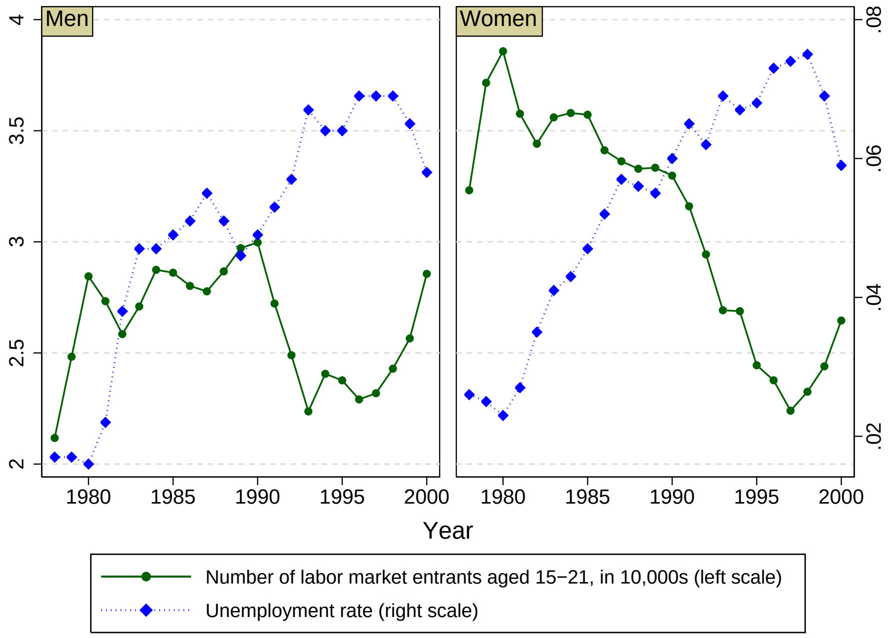
Figure 2: Fluctuation in regional unemployment rates



Source: Bundeskammer für Arbeiter und Angestellte.

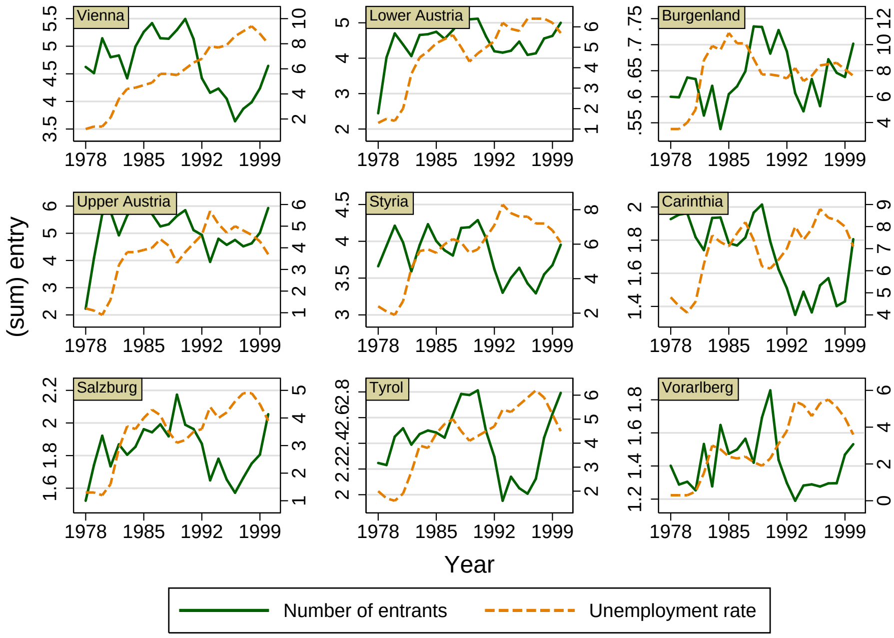
Figure 3: The number of labor market entrants



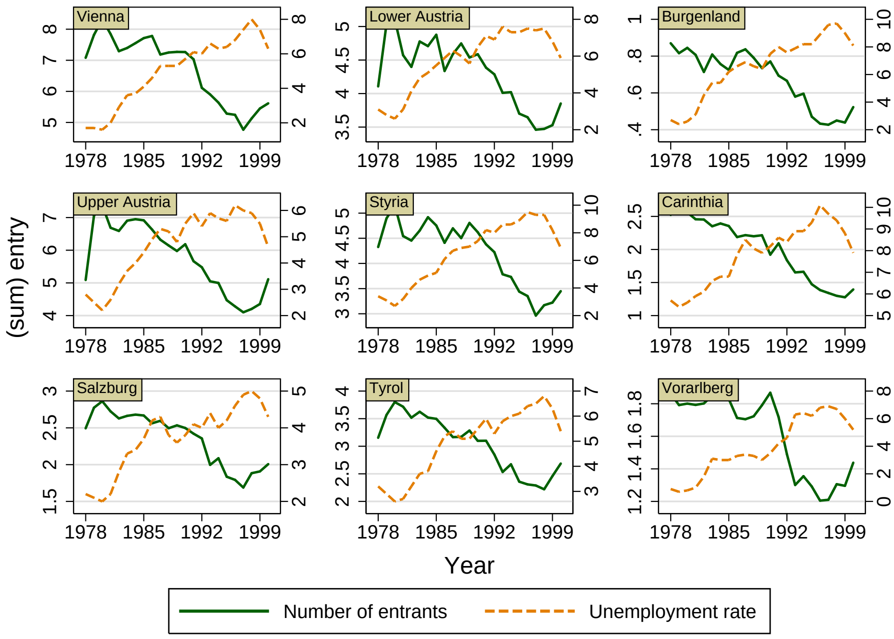


Sources: ASSD and Bundeskammer für Arbeiter und Angestellte.

Figure 4: Number of entrants and unemployment rate, by state



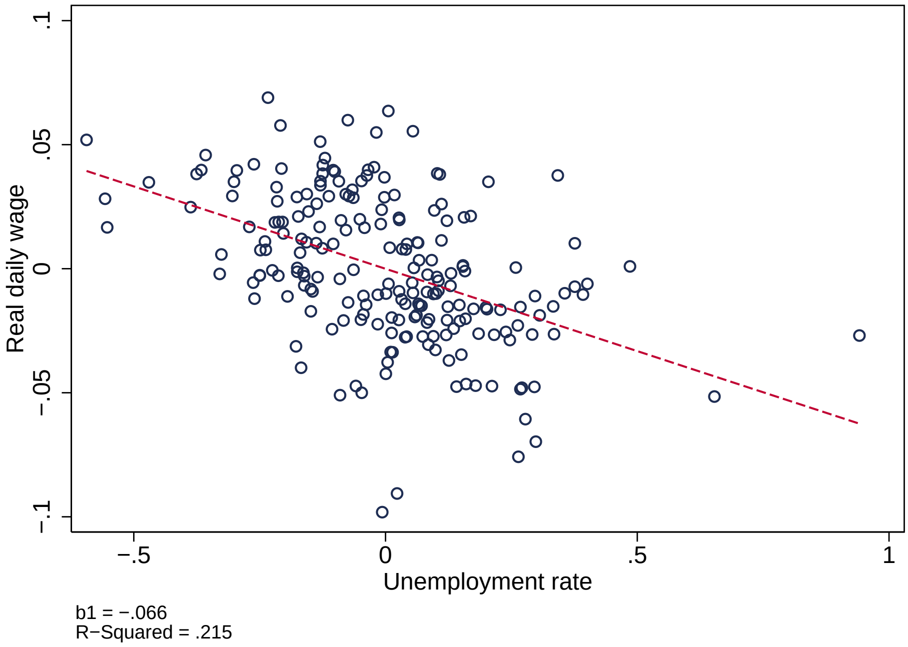
(a) Men



(b) Women

Notes:

Figure 5: Starting wage versus unemployment rate



Notes: The figure plots deviations from a simple quadratic time trend.

Figure 6: Starting wage versus unemployment rate

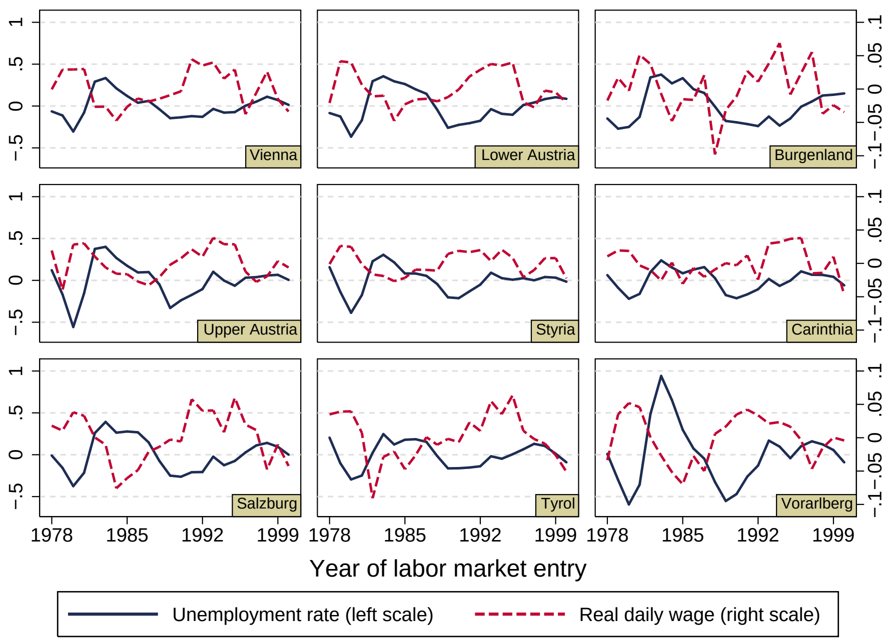
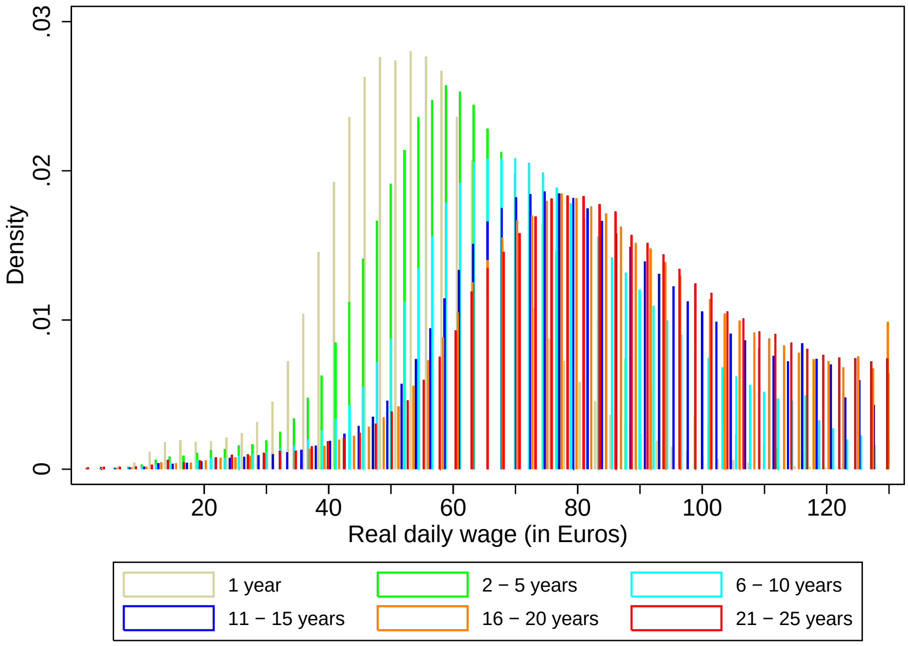
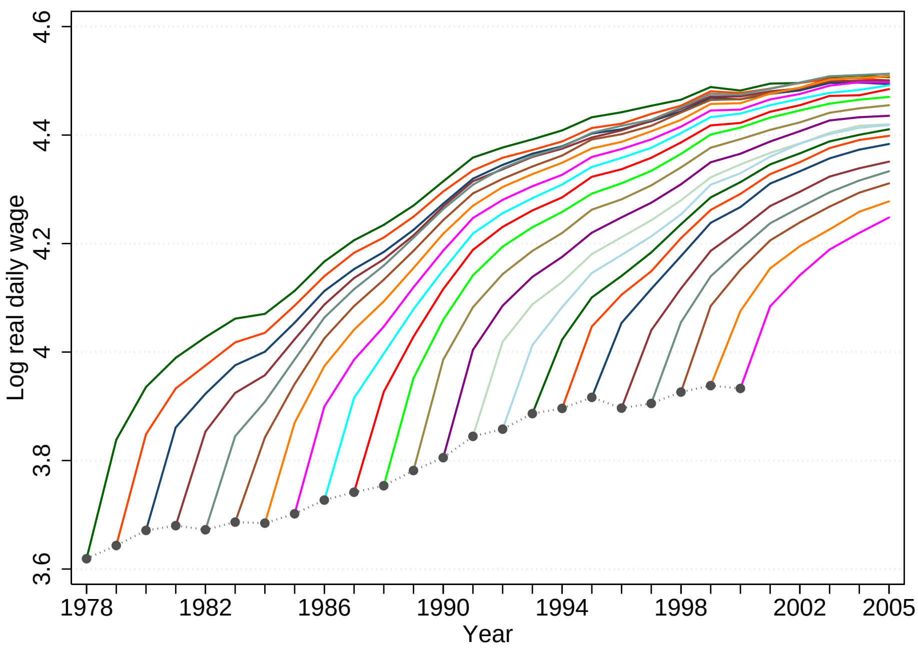


Figure 7: Wage distribution, by years of experience



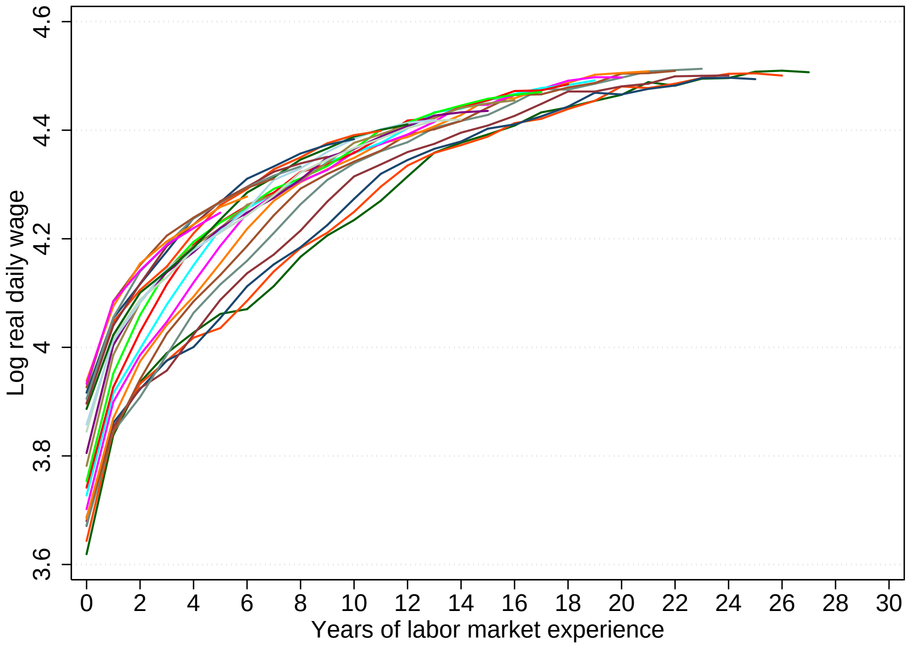
Notes: Observations equal to or above HBGr are excluded.

Figure 8: Wage profiles



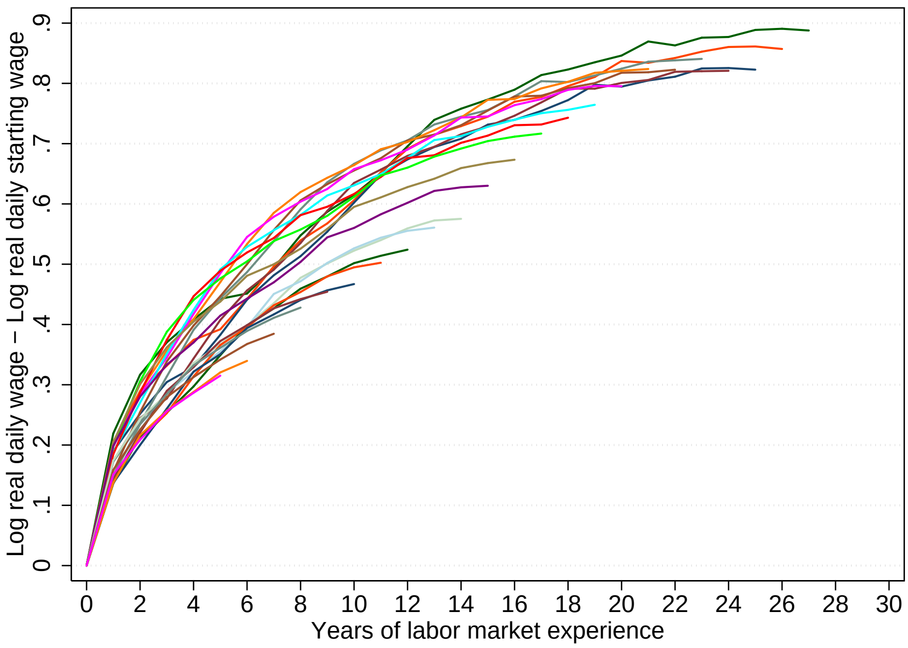
Notes:

Figure 9: Wage profiles over years of experience



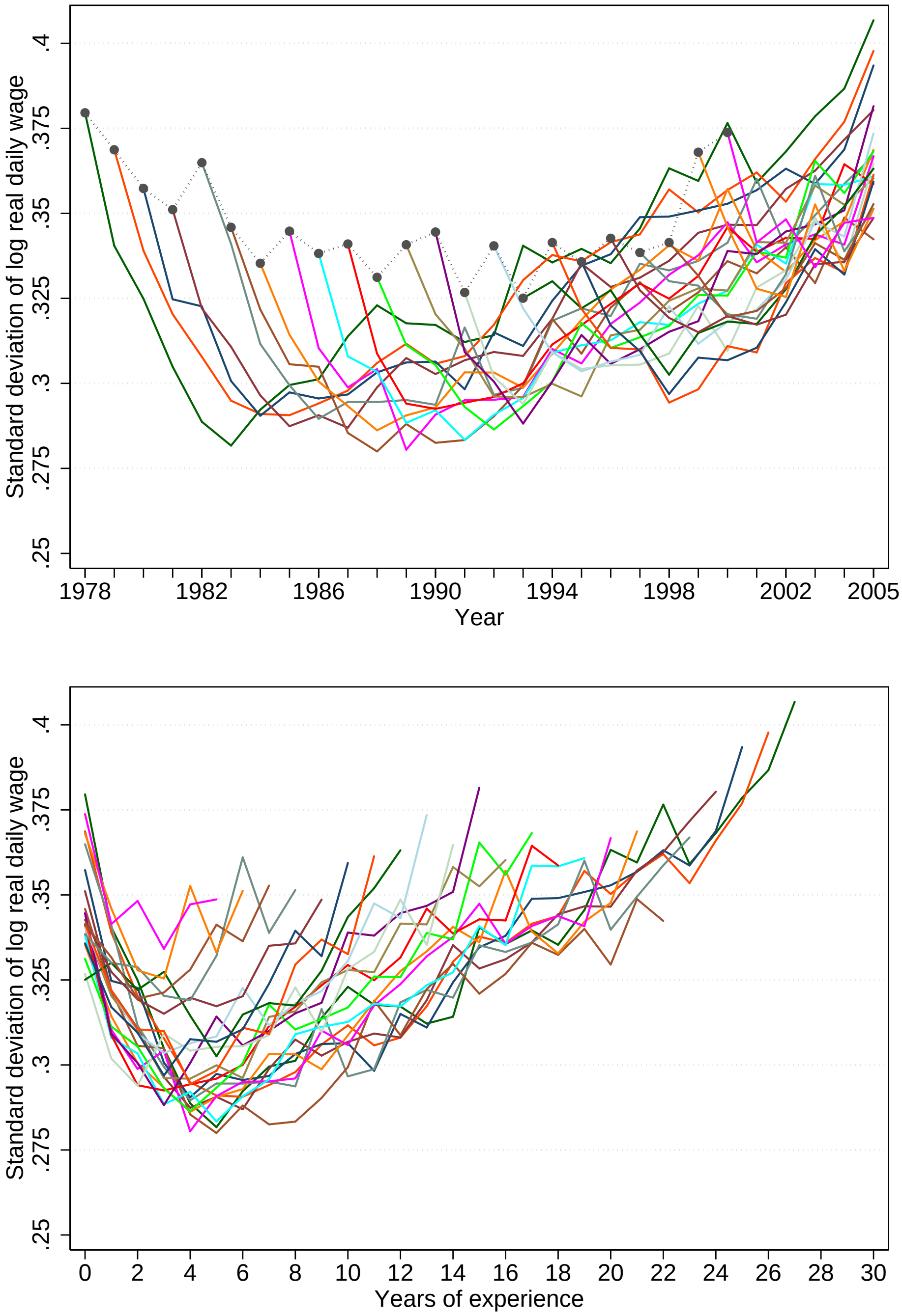
Notes:

Figure 10: Relative wage profiles over years of experience



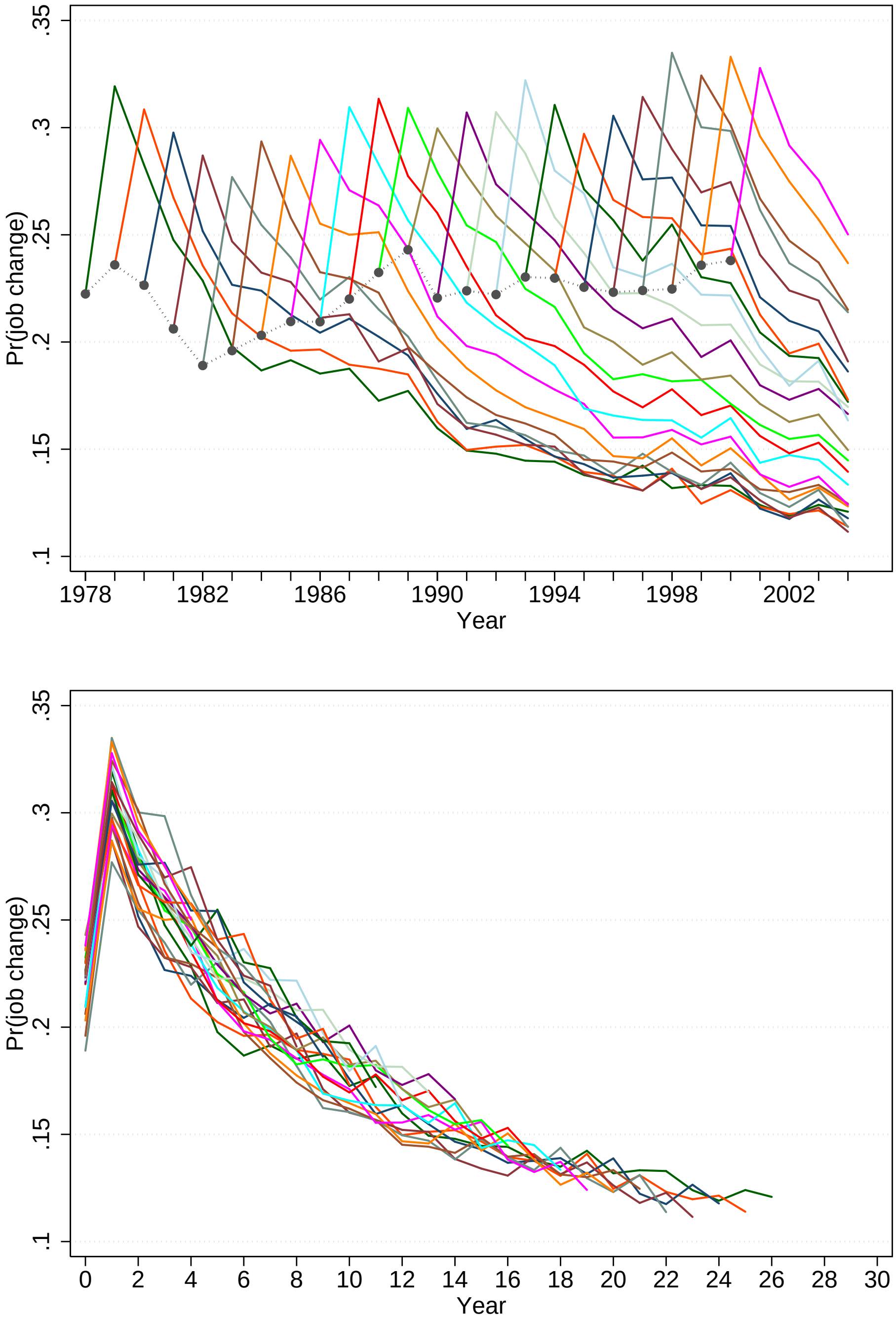
Notes:

Figure 11: Standard deviations



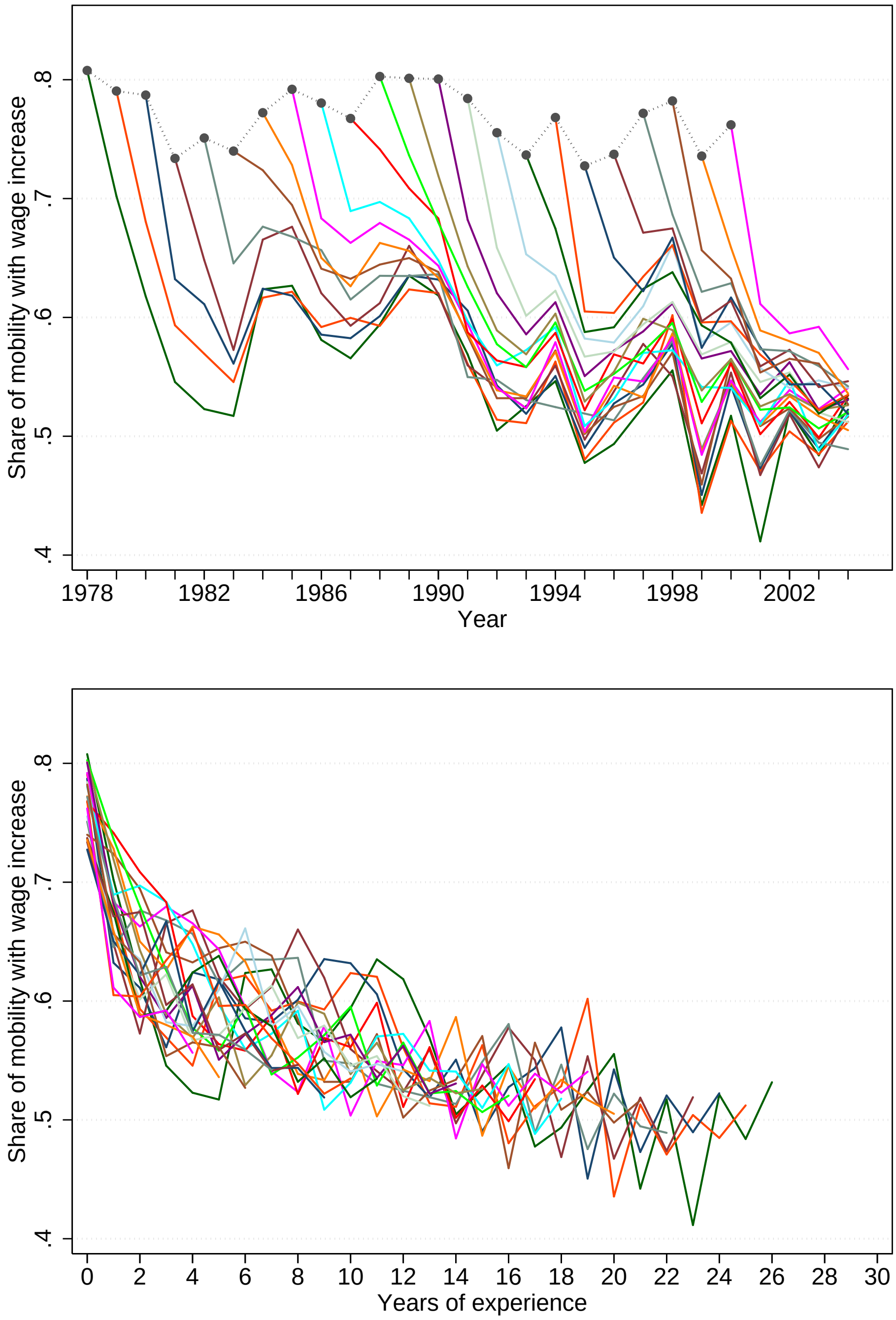
Notes:

Figure 12: Job mobility



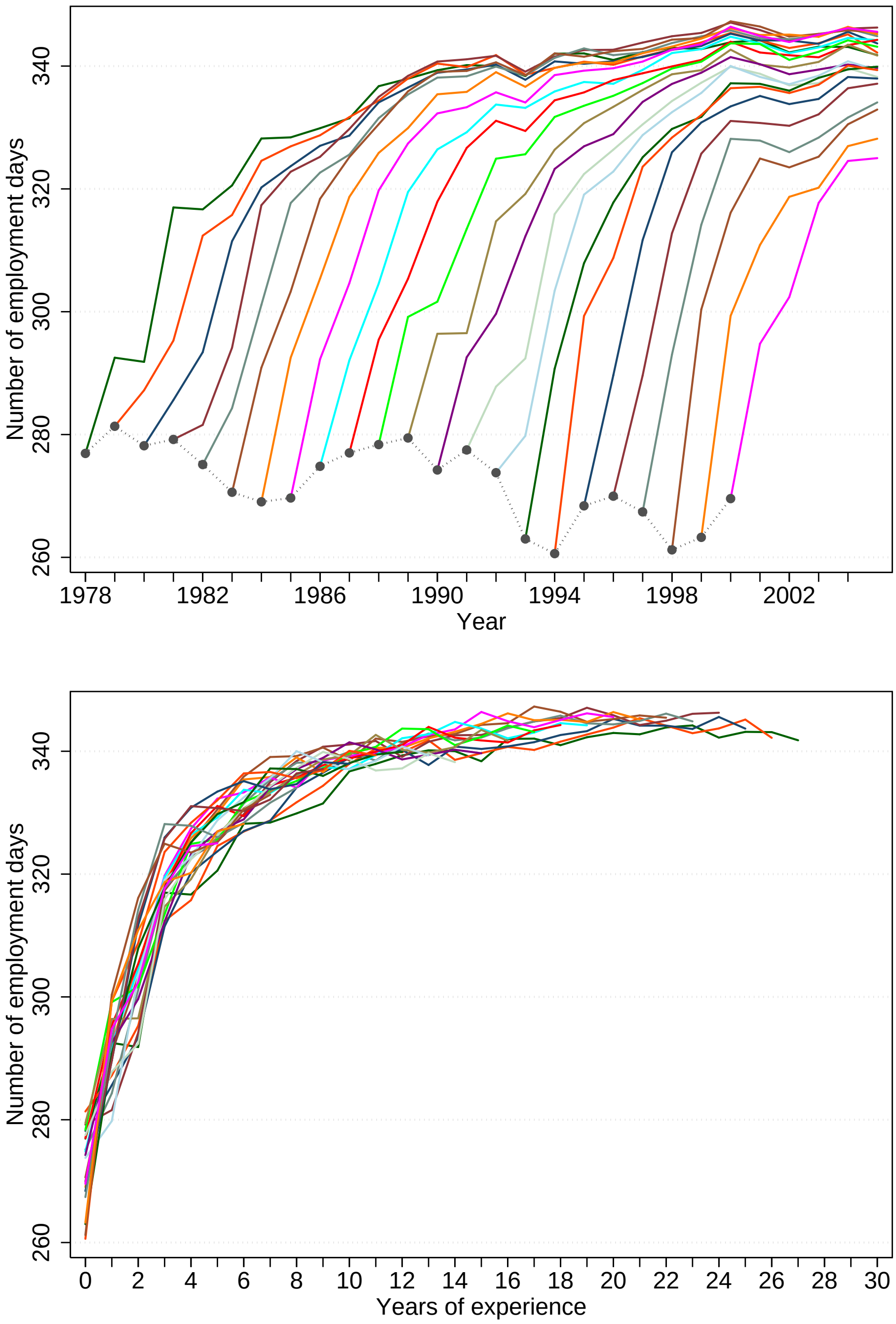
Notes:

Figure 13: Fraction of mobility associated with wage increase



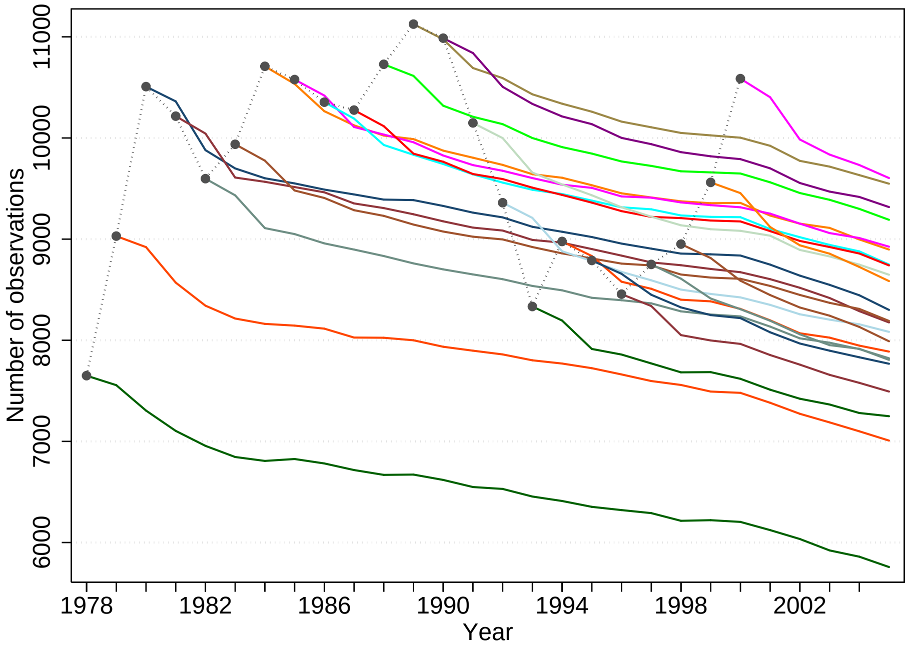
Notes:

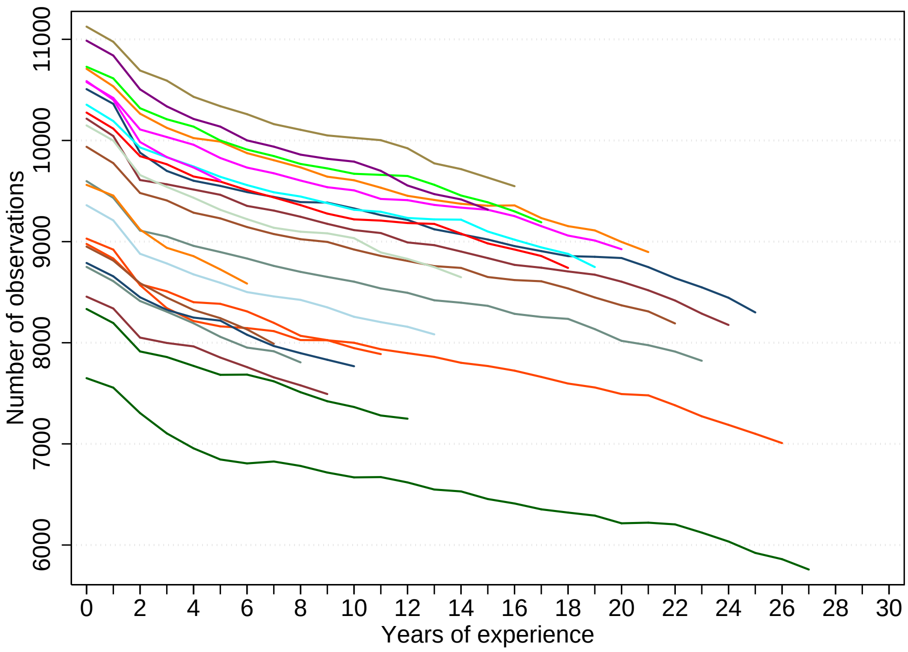
Figure 14: Number of employment days



Notes: First year (experience = 0) not shown in the lower panel.

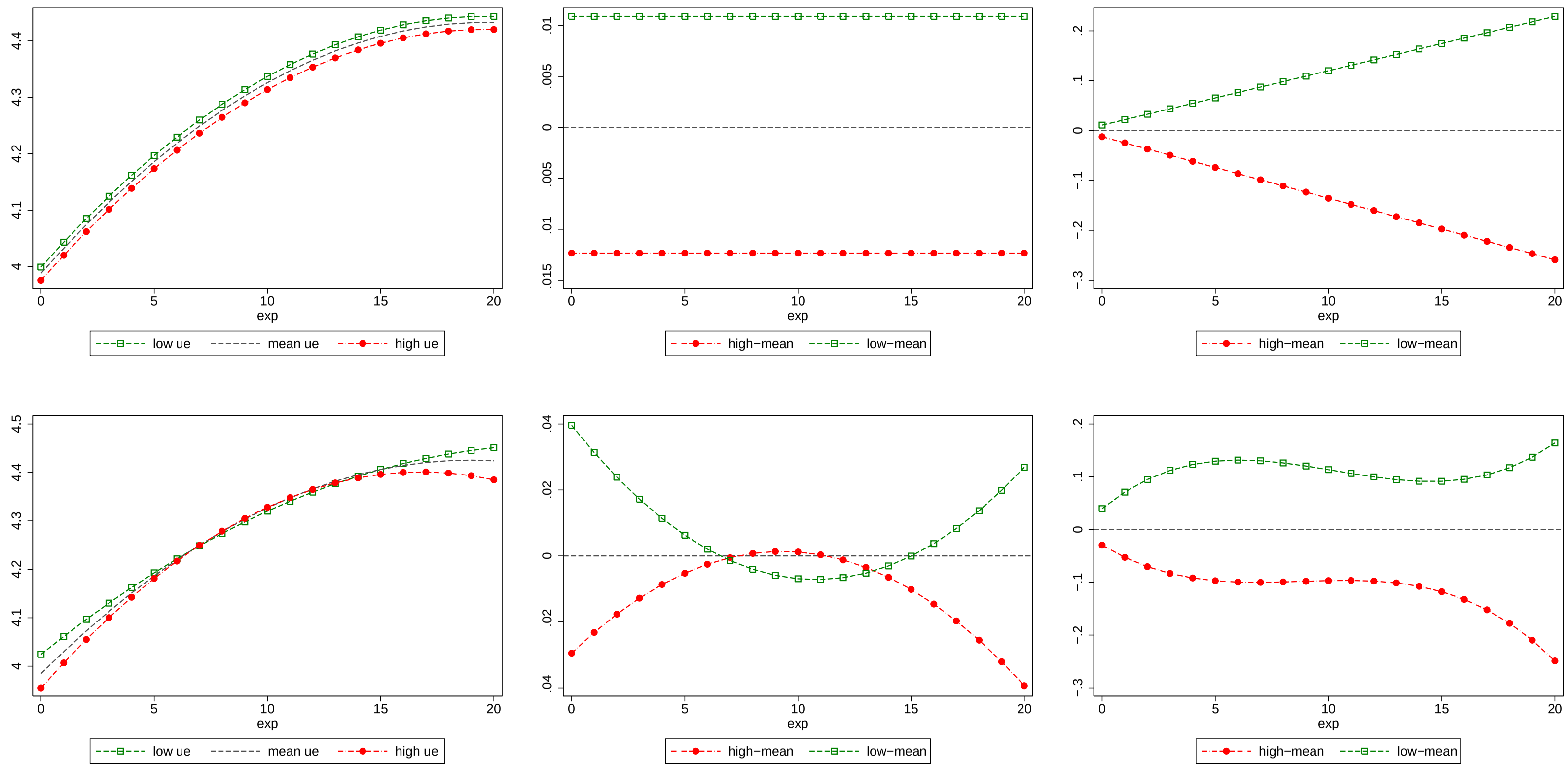
Figure 15: Number of observations





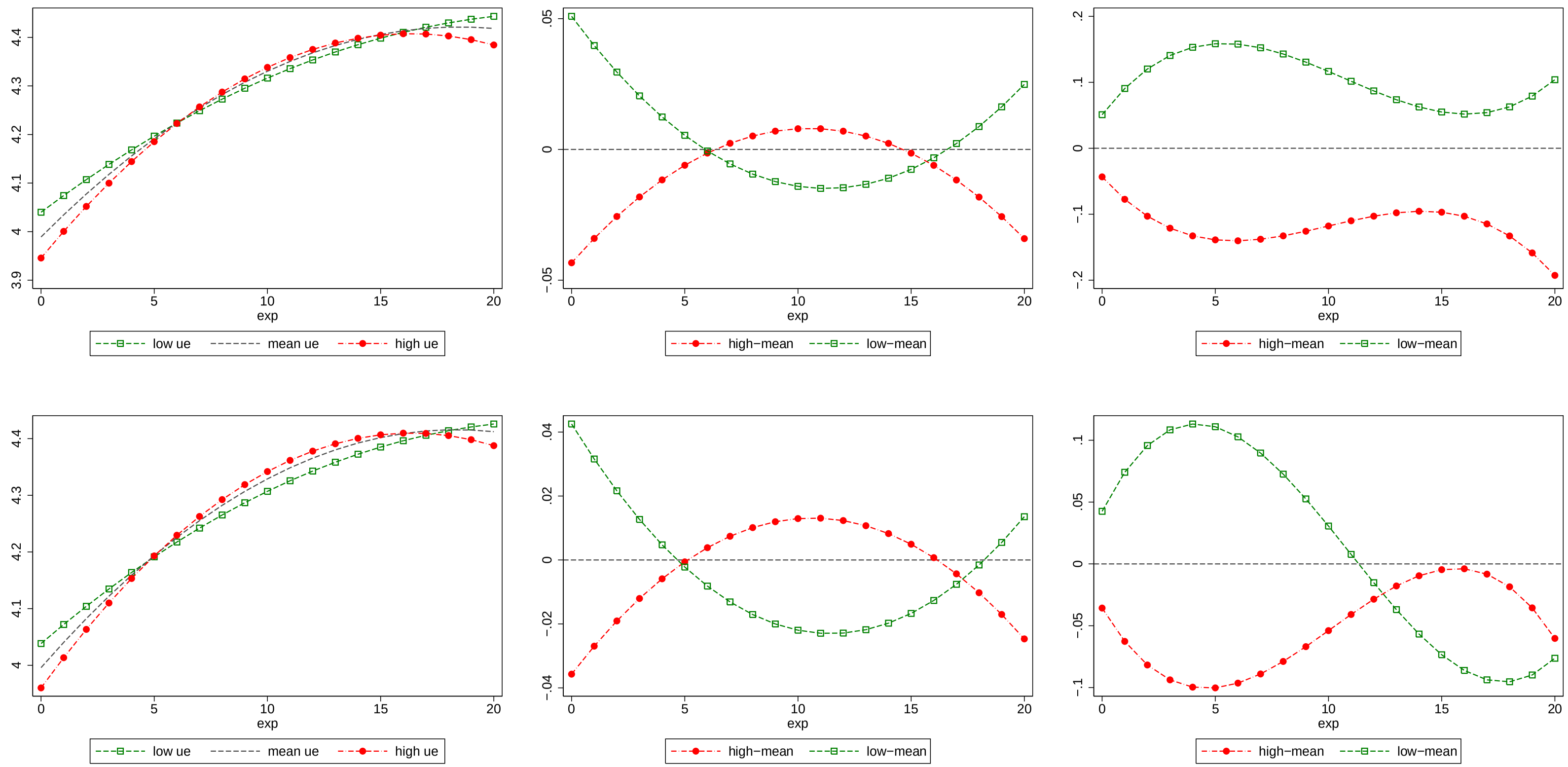
Notes:

Figure 16: Wage profiles, main results (models 1 & 2)



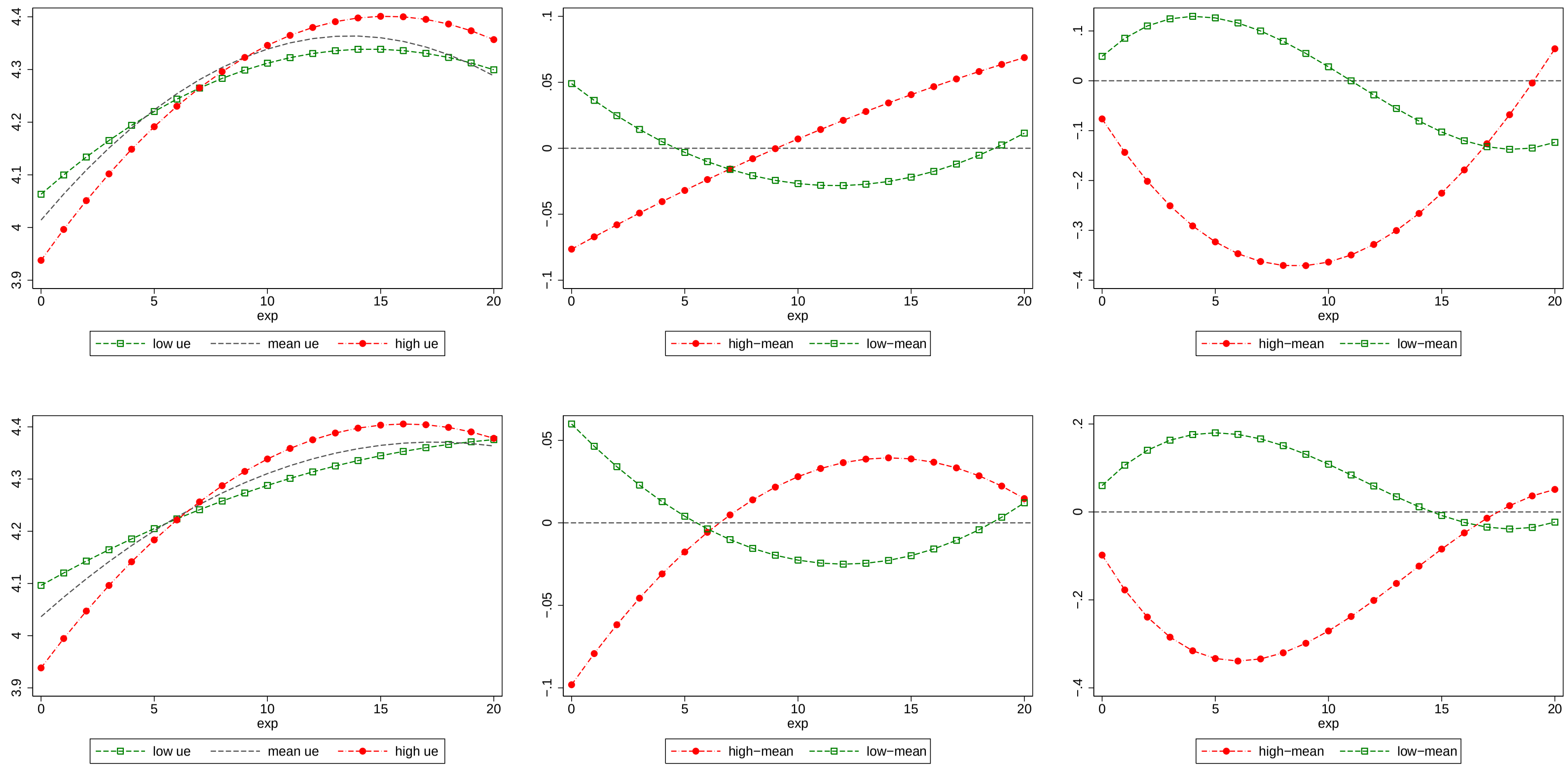
Notes:

Figure 17: Wage profiles, main results (models 3 & 4)



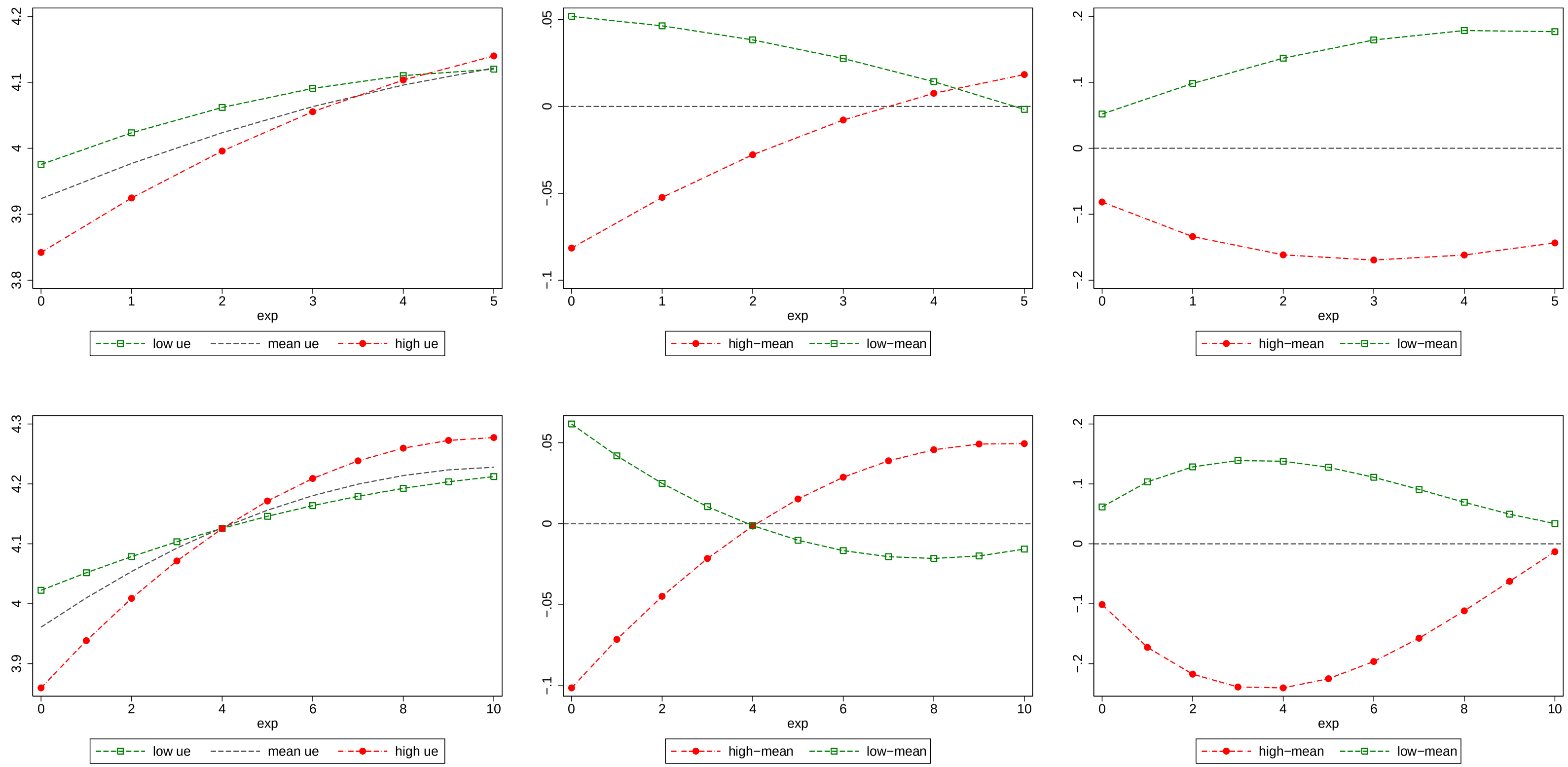
Notes:

Figure 18: Wage profiles, main results (models 5 & 6)



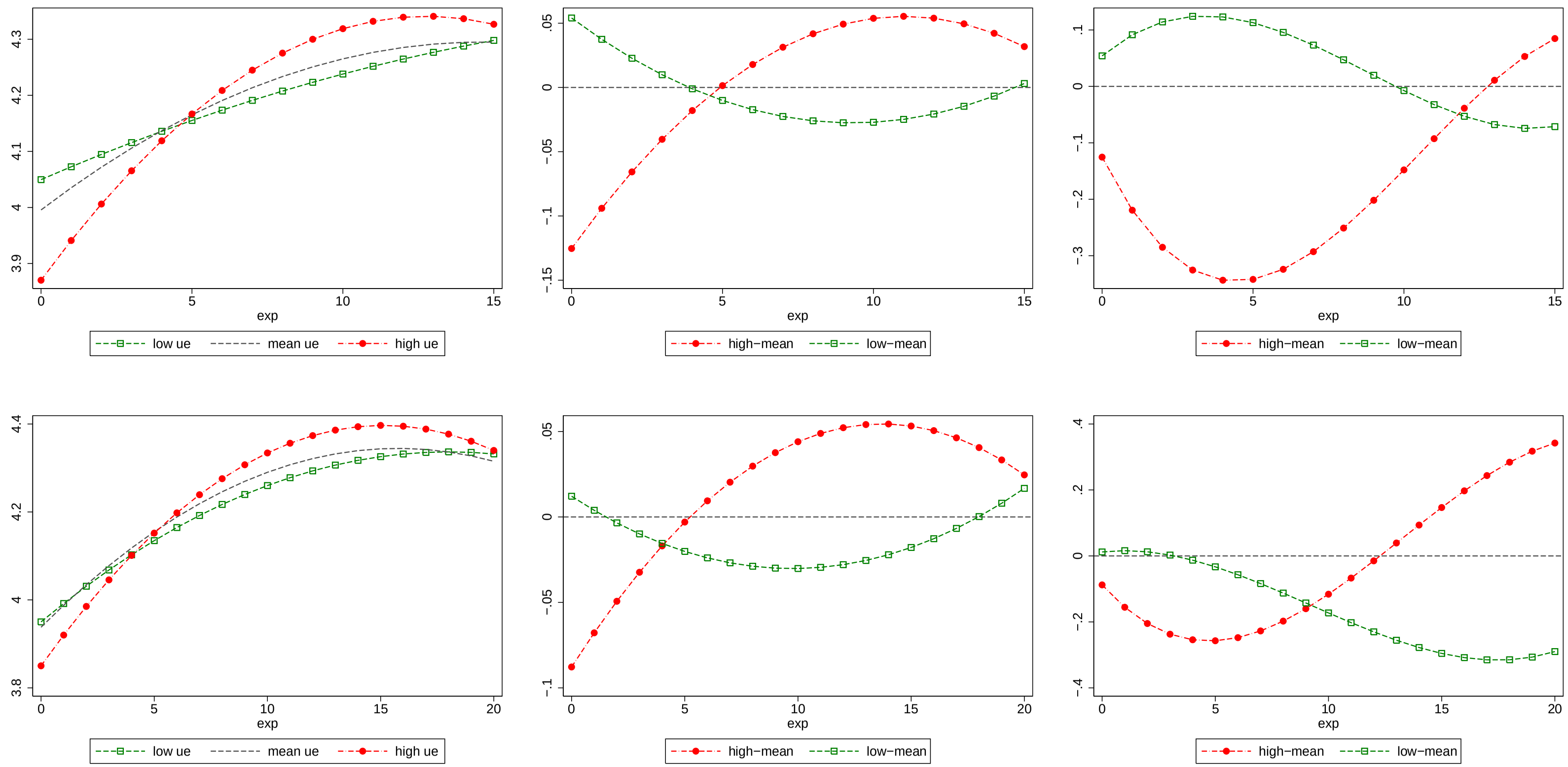
Notes:

Figure 19: Wage profiles, main results (by experience)



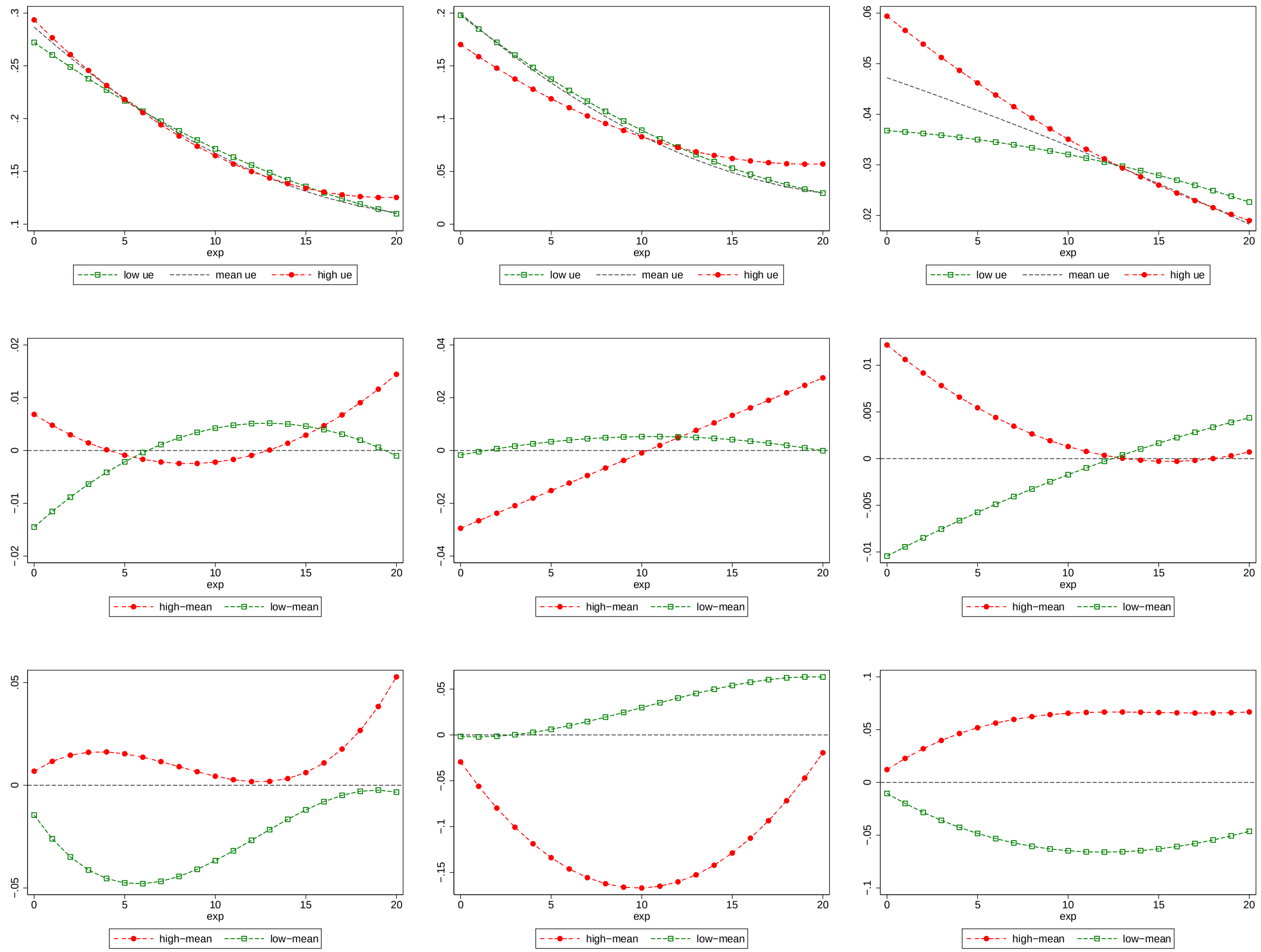
Notes:

Figure 20: Wage profiles, main results (by experience)



Notes:

Figure 21: Mobility profiles, main results (first year of experience excluded)



Notes:

A Data Appendix

Sample Construction

The sample used for the empirical analysis is constructed in three consecutive steps. First, we determine the start of the first regular employment spell (see below) for each individual born between 1957 and 1985 who is covered by the ASSD (to be covered, an individual must entitled to (future) social security benefits or must already have claimed social security benefits). The restriction on birth cohorts, in combination with the restriction on age age first entry that we apply below, ensures that the range of age at entry is the same for each year of entry considered in the analysis (1978-2000).

Second, we compute each individual's age at the start of his or her first regular employment spell starting between 1978 and 2000. We only consider those employment spells with a duration of at least 180 days as regular employment (3,344,863 observations). As detailed in the main text, the empirical analysis will focus on those individuals aged between 15 and 21 years at the start of their first regular employment spell. Additionally, we also drop all individuals who have at least once been self-employed and/or have worked as a farmer or as a civil servant, because such employment spells are not consistently covered by the data over the whole period of analysis and/or because earnings are not recorded (self-employed).

Third and finally, we take a simple 30% random sample from all remaining labor market entrants (for men and women separately, as the whole analysis is done for males and females separately) as the resulting number of observations in case of the panel data would be far too large in size. This procedure gives us a total of 486,067 unique individuals and yields 6,928,784 observations (= individuals $\times$ years) overall.

Key Variables

The ASSD includes very precise information about annual earnings and employment histories on a daily basis as the Central Social Security Administration collects these data for the calculation of old-age pension benefits. However, contributions are capped from above because there is a maximum level of old-age pension benefits. This essentially leads to right-censored wages in the data, as earnings above this threshold do not generate additional entitlements and are therefore of no interest to the Social Security Administration. However, as detailed in the main text, as we focus on individuals with lower education only, the problem of censored wages is mitigated to a significant degree.

Similarly, there is also a lower bound on earnings, below which not social security payments accrue. Say something about left-censoring. **give some more details**

Real daily wages (i.e. wages per workday) are in prices of 2007, include special payments (like 13. month) and are computed over all employers in a given year. Total earnings are then divided with the total number of days worked in a given year. In order to add firm characteristics for individuals who are connected with more than one single employer within year, we had to decide on a primary employer for each person-year combination. We decided to use the firm information from the employment relationship with the longest duration in a given year. All firm characteristics in the analysis therefore relate to the primary employer as defined only.

Estimating the Potential Number of Labor Market Entrants

Because we only observe individuals' actual labor market entry, the potential (i.e. maximum) number of labor market entrants is unknown. However, we can approximate this number by the size of the underlying birth cohorts.

We estimate these numbers in the following way. First, we extract the number of individuals covered by the ASSD for each year of birth. Although this does not correspond exactly to the actual size of birth cohorts (because individuals who will never enter the labor market will not show up at all in the data). We then compute the number of potential entrants aged 15 to 21, for each year from 1979 until 1997, as a weighted average of the corresponding birth cohorts.[22]

[22] For example, individuals born in 1957 turn age 21 in the year 1978. Similarly, individuals born in 1958 turn age 20 in the same year; and so on.

B Unobserved Heterogeneity and Time-Invariant Regressors

Assume we have the following model for the logarithm of the real daily wage:

$$\ln(y_{it}) = x_{it}\beta + z_i\gamma + \epsilon_{it}, \tag{B.1}$$

where x_{it} includes time-variant regressors and z_i consists of time-invariant regressors only. Most often we think of the error term as containing both an individual-fixed effect and an time-varying part assumed to be independent of the fixed effect (for the ease of exposition, we abstract from a time fixed effect):

$$\epsilon_{it} = \phi_i + \varepsilon_{it}$$

Most often, we are worried about potential correlation between the regressors and the individual fixed effect ϕ_i. Although the panel data methods usually applied in this case are able to eliminate ϕ_i, they are not applicable in our case because they also wipe off all time-variant regressors including our regressor of main interest, the unemployment rate at time of entry into the labor market (i.e. z_i is absorbed by ϕ_i, so that in general γ and ϕ are not identified simultaneously).[23] The standard panel methods for unobserved heterogeneity therefore estimate the parameters of the following model:

$$\ln(y_{it}) = x_{it}\beta + \phi_i + \varepsilon_{it} \tag{B.2}$$

To gauge the extent to which unobserved heterogeneity may be a problem in our analysis, we regress the estimated individual fixed effect (i.e. $\widehat{\phi_i}$ from equation (B.2)) on the time invariant regressors contained in z_i which enters in equation (B.1):

$$\widehat{\phi_i} = z_i\delta + \epsilon_i, \tag{B.3}$$

where each individual only appears as a single observation. We think that this regression provides valuable insight into the nature of ϕ_i as well as our ability to control for the relevant part of ϕ_i using time-invariant variables only. Moreover, it gives us some interesting insight into what $\widehat{\phi_i}$ means in our specific application. Results are given in table B.1.

Tables B.1 and **??**

Again, we show results for both the overall sample as well as the balanced sample, separately for men (table B.1) and women (table **??**). The first model (columns 1 and 4) only includes an individuals' rank within the distribution of starting wages and our proxy for education (i.e. age at entry into the labor market). We believe that these are the two variables that most closely relate to unobserved heterogeneity at the individual level. The second model adds the two key regressors at the aggregate level, both of which relate to a specific year of labor market entry. Finally, the third model adds additional variables describing the first regular job of an individual (i.e. region and industry of first employer).

Quite interestingly, for males, the two first variables alone can explain about 20% of the total variation in the fixed effects (about 10% for females). If we additionally include the number of entrants and the initial unemployment rate the explained variation almost doubles, so that about a third of the variation in unobserved heterogeneity can be explained by these four variables (six regressors) alone. Again, the explanatory power is lower for women than for men, but we are still able to explain about 12% to 25% using the same set of six regressors only. If we additionally include

[23] Hausman and Taylor (1981) proposed a method which allows for both unobserved heterogeneity and time-invariant regressors.

Table B.1: Fixed effect versus time-constant regressors

	u[svnr]	u[svnr]	u[svnr]	u[svnr]	u[svnr]	u[svnr]
Mean	0.050	0.050	0.050	−0.011	−0.011	−0.011
Standard deviation	0.299	0.299	0.299	0.248	0.248	0.248
rank	0.308***	0.358***	0.444***	0.306***	0.332***	0.431***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
age at start of first regular job	0.056***	0.032***	0.027***	0.040***	0.028***	0.021***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
ln_entry_15to21		0.325***	0.168**		−0.226***	1.508***
		(0.025)	(0.078)		(0.028)	(0.112)
ln_entry_15to21_sq		−0.020***	−0.016***		0.017***	−0.082***
		(0.002)	(0.005)		(0.002)	(0.007)
ln_alq0		0.097***	0.091***		0.061***	0.057***
		(0.002)	(0.002)		(0.002)	(0.002)
ln_alq0_sq		0.055***	0.086***		0.025***	0.038***
		(0.001)	(0.001)		(0.001)	(0.001)
Constant	−1.179***	−2.344***	−1.361***	−0.921***	−0.116	−7.634***
	(0.010)	(0.099)	(0.316)	(0.010)	(0.112)	(0.455)
Region at entry	No	No	Yes	No	No	Yes
Industry at entry	No	No	Yes	No	No	Yes
Occupation at entry	No	No	Yes	No	No	Yes
n	223, 899	223, 899	223, 899	131, 859	131, 859	131, 859
k	2	6	30	2	6	30
Adjusted R-Squared	0.187	0.342	0.428	0.221	0.294	0.373
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000

Notes: