DISCUSSION PAPER SERIES

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IZA DP No. 8159

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April 2014

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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Discussion Paper No. 8159
April 2014

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IZA Discussion Paper No. 8159
April 2014

ABSTRACT

The Lifetime Earnings Premium in the Public Sector: The View from Europe*

In a context of widespread concern about budget deficits, it is important to assess whether public sector pay is in line with the private sector. Our paper proposes an estimation of differences in lifetime values of employment between public and private sectors for five European countries. We use data from the European Community Household Panel over the period 1994-2001 for Germany, the Netherlands, France, Italy and Spain. We look at lifetime values instead of wage levels because, as we show in our results, differences in earnings mobility, earnings volatility and job loss risk across sectors occur in many instances and these will matter to forward-looking individuals. When aggregated into a measure of lifetime value of employment in either sector, these differences yield estimates of the lifetime premium in the public sector for these five countries. We also present differences in the institutional and labour market structures in these countries and find that countries for which we estimate a positive lifetime premium in the public sector, i.e. France and Spain, are also the countries where access to the public sector requires costly entry procedures. This paper is to the best of our knowledge the first to use this dynamic approach applied to Europe, which we are able to do with a common dataset, time-period and model.

JEL Classification: J45, J31, J62

Keywords: income dynamics, job mobility, public-private inequality, selection effects, institutions

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* We would like to thank two anonymous referees and the editor for their helpful comments and also thank participants at the EALE/SOLE conference 2010, and seminar participants at CMPO and the University of Sheffield. Matt Dickson thanks the ESRC for funding this research under grant PTA-026-27-2132.

1 Introduction

The public sector wage bill accounts for about a fifth of government spending across most European countries.[1] In a context of widespread concern about budget deficits and policies implemented to reduce the size of government expenditure, it is important to assess whether public sector pay is in line with the private sector.[2] Comparisons of pay conditions between the public and the private sector matter for several reasons: the public sector wage bill being paid out of taxpayers' money makes it a politically sensitive issue; public sector pay being to some extent insulated from market forces may drive a wedge between public and private remunerations and increase inequality; finally, were public sector pay to become relatively unattractive, recruitment and retention in the public sector workforce would become difficult. Our paper proposes an estimation of differences in lifetime values of employment between public and private sectors for five European countries.

We show that the comparison of lifetime values instead of wage levels is relevant because dynamic differences in earnings mobility, earnings volatility and job loss risk across sectors occur in many instances and these will matter to forward-looking individuals. While a large body of literature has examined differences across sectors in terms of pay levels or pension systems (see Emmerson and Jin (2012) for a recent contribution), very little attention has been given to the comparison of lifetime values aggregating the various dimensions of differences into a single measure relevant to individual sector choice. Moreover, we document differences in institutional settings regarding public sector pay, progression, employment and pension systems across the countries we study and find interesting correlations between barriers to entry into public sector jobs and lifetime premia. While it is beyond the scope of this paper to propose and estimate a theoretical mechanism linking institutions and lifetime premia, we claim that the cross-country comparison that we carried out is a useful step for future research aiming to model the existence of a (partial) equilibrium lifetime premium as a result of sector-specific institutions.

In terms of method, we use the estimation strategy proposed in Postel-Vinay and Turon (2007) to estimate jointly the four components of the public-private "premium", namely levels, mobility and volatility of earnings and job loss risk while controlling for selection between sectors according to observed and unobserved characteristics. We use data from the European Community Household Panel over the period 1994-2001 for Germany, the Netherlands, France, Italy and Spain.[3] We find evidence of marked differences

[1] See section 3.1 for detailed figures.

[2] See for example Giordano et al. (2011) and Glassner (2010) for recent European reports on public sector pay.

[3] More on why these countries and no others were used in section 4 below. The focus on a "pre-crisis" period allows us to assess the differences of interest before various policies were put in place to alter one dimension or another of public-private

between the public and private sectors with regard to earnings mobility, earnings volatility and job loss risk, as well as earnings levels. When aggregated into a measure of lifetime value of employment in either sector, these differences yield estimates of the lifetime premium in the public sector for these five countries. In order to put these differences into their institutional context, we also present differences in the institutional and labour market structures in these countries that may translate into the dynamic differences that we estimate. This paper is to the best of our knowledge the first to use this dynamic approach applied to Europe, which we are able to do with a common dataset, time-period and model.

Our main findings can be summarised as follows. We find substantial cross-country disparities in lifetime public premia as well as differences in institutional settings with respect to public sector recruitment and pay determination. We show evidence of significant unobserved heterogeneity, both in terms of labour market mobility and earnings levels and dynamics. After controlling for selection, sizable differences are found in the following dimensions and countries: cross-sectional incomes are 11 log-points higher in the public sector than in the private sector in Spain, 3 log-points higher in France and 4 log-points higher in Italy. The dispersion of public sector incomes is substantially lower than their private sector equivalent in the Netherlands and Spain, while public sector incomes are more persistent in Italy. Returns to experience are higher in the public sector in Germany but lower in Italy and Spain. Finally, contrary to public perception, job security is not significantly greater in the public sector once selection is taken into account. The job loss rate is actually *higher* in the public sector in Germany than it is in the private sector.

When aggregated into lifetime values (the construction of which we describe below), the above components yield substantial positive premia in the middle and lower parts of the distribution of lifetime values in France and Spain. However, workers at the top of the distribution in the Netherlands are worse off in the public sector in the long term. The cross-sector difference in income inequality in Spain appears to be related to the transitory component of earnings, whereas for Germany and the Netherlands it is a more permanent feature of the distributions.

Putting these results in the context of local institutions offers plausible causal mechanisms behind the existence of a public sector lifetime premium. In France and Spain, substantial barriers to access to public sector jobs are in place in the form of demanding and lengthy entry examinations. These are also the countries where we find significant lifetime premia in the public sector. While we do not claim to show any causal effect between these two observations, we note that they are consistent with a partial structural model of individual sector choice based on lifetime values and cost of public sector entry.

differences in pay, employment and pension conditions.

The paper proceeds as follows: the related literature is reviewed in the next section, followed by a description of the institutional context of each country in section 3 and a descriptive analysis of each country's data in section 4. The statistical model to be estimated is detailed in section 5, with the results analysed in section 6. The lifetime values of employment in each sector are computed in section 7 allowing us to contrast the public-private differences accounting for earnings and job mobility with straightforward cross-sectional earnings differences. How these findings relate to the labour market structures in each country is considered in section 8 before section 9 concludes.

2 Related Literature

This paper relates to two different literatures: the public-private pay differences literature, and the literature on income mobility and lifetime inequality. Within the public-private literature, this paper contributes by presenting an application of this dynamic modelling approach and by deriving a set of estimates of public-private pay gaps across a number of major European countries, estimated with a common model on data from a homogenized, multi-country longitudinal data set. Relating countries' lifetime premia to their institutional and labour market structures offers a plausible explanation for our findings, especially since we can rule out dataset, time-period or modelling approach as the source of any differences.

As noted in the introduction, the vast majority of the public-pay gap literature concentrates on cross-sectional differences in wages and on the extent to which these can be explained by non-random selection into sector. In the UK for example, Disney and Gosling (2003) show that the raw public premium in male earnings is high, however when they use an instrumental variables approach – exploiting privatization to control for selection into the private sector – the premium becomes insignificant.

For Germany, Dustmann and van Soest (1998) estimate that public sector wages are lower for all age and education groups but that this gap decreases with both age and education. They obtain very different results however if they do not take account of the endogeneity of sector choice or if the selection equation to take account of the endogeneity is only weakly identified. In addition they find that individuals who are observed in the public sector would have higher average earnings if they were to move to the private sector. However these workers' negative public premium is smaller than would be the case for those workers observed in the private sector – suggesting that workers do self-select into the sector where they have a comparative advantage. These results support the author's earlier findings for German males (Dustmann and van Soest (1997)).

More recently Melly (2005) has used quantile regression techniques and similarly found that conditional wages in Germany are lower in the public sector for males, and that the conditional distribution of wages is more compressed in the public sector – a finding that is common throughout the literature for many countries. Melly suggests that the public sector effect on wages is not uniform across the wage distribution, with differences in observable characteristics explaining more of the public-pay gap at the top of the distribution, and differences in unobservables explaining more at the bottom. This highlights the need to control for unobservable characteristics and their influence on sector selection and wages.

For the Netherlands, Hartog and Oosterbeek (1993) deal with the endogeneity of sector choice by using an endogenous switching model to estimate public-private pay differentials. They refute earlier Dutch evidence of public sector underpayment, concluding that public sector workers earn more in the public sector than they would in the private sector while the reverse is true for private sector workers, indicating that workers sort into the sector affording them a comparative advantage. Similarly Van Ophem (1993) uses a modified endogenous switching model and finds that while some categories of public sector workers earn more than corresponding workers in the private sector, there are several categories of employment – both higher and lower skilled – in which the public sector offers a substantial negative premium.

Bargain and Melly (2008) have used a large sample from the French Labour Force Survey – a rotating panel in which individuals are included for three successive years, with one third of the sample replaced each year – to estimate the public-private pay difference. They use both a standard fixed-effects estimator to control for selection and also implement a fixed-effects quantile regression model to evaluate the public premium at different quantiles of the distribution. They find that in France on average men select negatively into the public sector but that the public premium becomes zero once selection on unobservables has been accounted for. The quantile regression results suggest that the often-found result of pay compression in the public sector is partly due to positive selection of men into the public sector at the bottom of the distribution, but negative selection into the public sector at the top of the distribution. Blue-collar workers appear to benefit from a positive public-sector premium, while the white-collars face a negative public premium.

Lassibille (1998) decomposes public-private wage differentials in Spain into the contribution of differences in worker characteristics and differences in the returns to those characteristics, using separately estimated wage functions that control for selection into sectors. He finds that the public sector pays lower returns to education and experience, and thus the earnings advantage in the public sector is higher for the lower skilled but tapers off as one moves up the skill distribution. Lassibille also concludes that differences in worker characteristics are more important than differences in the returns to these characteristics in explaining the public pay gap, and that there is a public sector 'mark-up' in wages that is unrelated to characteristics, generally offsetting the lower returns on human capital.

Explicit cross-country comparison of public-private wage differentials is rare, however Lucifora and Meurs (2006) investigate public-pay gaps in Britain, France and Italy using non-parametric (kernel) and quantile regression methods. For France and Italy they conclude that the private sector use of collective bargaining and union power results in a pay setting system based heavily on rewarding observable characteristics (education, experience), which can explain the most part of the public sector wage gap. The quantile regression analysis echoes Melly's findings for Germany, suggesting that as one moves up the distribution, the proportion of the pay gap explained by observable characteristics increases, whereas in the lower quintiles differences in unobserved characteristics are more important in explaining pay differences. These results for France and Italy are corroborated by Ghinetti and Lucifora (2007) using ECHP data from the final wave, 2001.

Nevertheless, though these studies are informative and in some cases deal with the endogeneity of sector choice through either functional form assumptions (Van Ophem, 1993) or an instrumental variables approach (Dustmann and Van Soest, 1998; Hartog and Oosterbeek, 1993), they consider only cross-sectional differences in instantaneous earnings between sectors. This is equally the case for those studies based on a quantile regression approach.

Cappellari (2002) is the only other study (bar Postel-Vinay and Turon (2007)) to address differences in earnings dynamics between the public and private sector. He uses a panel of Italian administrative data and controls for unobserved individual heterogeneity in earnings levels and earnings growth rates. In the analysis, Cappellari considers cross-sector differences in the autocovariance structure of log wages, finding that there is lower earnings dispersion in the public sector yet greater persistence: thus while inequality is lower in the public sector, initial earnings differences persist over the lifecycle. However he deals with the public and private sectors separately, thus imposing the assumption of exogenous selection of individuals into sectors and taking no explicit account of transitions between sectors or into unemployment. As many studies attest to the critical importance of non-random sorting of workers across sectors, we model the employment dynamics alongside the earnings dynamics in order to form a more complete picture.

This paper also relates to the vast literature on empirical models of income dynamics and their application to the study of lifetime income inequality. Within this broad literature there are a number of approaches, though the majority of contributions (including ours) use flexible reduced-form models of either absolute or relative earnings mobility to decompose the earnings process into a permanent and a transitory component. Differences between individuals in the permanent component are interpreted as a measure of lifetime inequality (see *inter alia* Lillard and Willis, 1978; Gottschalk and Moffit, 1993; Gottschalk, 1997; Bunchinsky and Hunt, 1999; Bonhomme and Robin, 2009). A second line of attack is to take a more structural approach derived from job search theory and analyse inequality in lifetime values and how this inequality has evolved over time (see Bowlus and Robin, 2004; Flinn, 2002). While each of these papers contributes to the body of evidence on lifetime inequality in earnings, none of them consider lifetime differences between job sectors.

So while there is a large literature considering the public-private pay gap in a *cross-sectional* context, controlling for the non-random nature of sector choice, and a large literature considering lifetime inequality in earnings using dynamic models, the marriage of the two is very rare, a gap that this paper fills for Europe.[4]

3 Institutional Context

Differences in wage setting practices, contract types, entry requirements, career pathways and pension provisions between the public and private sectors impart different dynamics and affect the public-private gap in both pay and lifetime values. Thus differences between these factors across countries may relate to the differences in public premia in earnings and lifetime values that we find. Below we describe the similarities and differences in these various dimensions between the public and private sectors and across countries.

3.1 Wage Setting

It is generally the case that various political, institutional and economic factors interact to explain the determination of public and private sector wages. Each sector has different characteristics and is bound by different forces: the private sector is subject to profit constraints, whereas the public sector is governed by political considerations and budgetary imperatives. The degree of unionisation, the extent of collective bargaining and the ease of measuring productivity are examples of areas that affect pay determination differentially across the sectors. Moreover, the government may want to set an example as an employer and therefore be motivated to pay higher wages to its lower skilled employees than would be found in the private market. It may also be reluctant for political reasons to pay the high levels of wages to higher-skilled workers that are found in the private sector, especially given the other favourable characteristics of public sector employment. Working for the state has been associated with certain privileges and a coveted status,

[4]The 'gap' in the literature for the UK having been addressed by the earlier Postel-Vinay and Turon (2007) paper.

especially for those public employees who are civil servants – hence the remuneration, especially at the top, is not all in terms of wages. This general characterisation broadly captures the situation in each of the countries in our data.

In light of potential concerns about privatisations and changes over time, it is worth noting that throughout the period of our data (1994-2001) the size of the public sector wage bill – in terms of percentage of GDP and percentage of overall government spending – remains stable within each country.[5] Though there were institutional changes implemented in many European countries during the 1990s – aimed at increasing competition and efficiency in the public sector – it remained the case that the rules determining pay and conditions differed significantly between the sectors (see Giordano et al, 2011). However, despite the differences between sectors, there is a great deal of commonality across countries in wage setting, particularly in the public sector.

Indeed, cluster analysis of wage setting institutions for both sectors, performed by the European Central Bank, finds that France and the Netherlands plus Germany and Italy all fall into the same group who exhibit a broadly regulated system of wage bargaining (see Du Caju et al, 2008). The system is characterised by a high level of collective agreement coverage, the dominance of sector level wage bargaining and the absence of coordination other than through minimum wages. France and the Netherlands differ from Germany and Italy in that there were national minimum wages in the former countries but not the latter. Spain falls into a slightly different category which exhibits the same general characteristics as above, including a national minimum wage, only in addition indexation, inter-sectoral agreements and the role of the government are even more important in wage setting. The countries in our data showed little sectoral and time variation in wage setting institutions over the time period of our data, there was little change in average agreement length (which ranged from one year in the Netherlands, 1.5 years in France, through to 2.5 in Germany) and overall the wage bargaining institutions were rather stable and relatively untouched by labour market reforms (see Du Caju et al, 2008).

Compared with the UK, the nations we consider all have strongly regulated labour markets, impacting both the public and private sector wages. Civil servants pay is set by law in each country, while collective bargaining determines pay agreements at the national level in other public sector jobs and in the private sector, with most employees in each country covered by a collective agreement. There is no automatic indexation of public sector wages to prices in any of the countries, rather public sector wage growth is

[5]For Germany and the Netherlands the public wage bill was 8-9% of GDP, for France, Italy and Spain it was slightly higher at 10%. As a proportion of total government spending, in France and Spain the public wage bill is almost 25%, whereas in Italy it is around 20%, lower still in the Netherlands, 18%, and Germany, 15% (see Tepe, 2009).

determined by bargaining with reference to productivity (at company level) and developments in the macro economy and budgets (at national negotiation level). For all of the countries in our data public sector wages are set at the national level.[6] Germany, France, Italy and Spain have very rigid and deterministic pay scales for civil servants according to the hierarchical level, corps, grade and particular post. While in the French and Italian systems pay can reward effort via the bonus structures, the Spanish civil service pay system explicitly allows some performance-related element. In the private sector, France differs slightly in that the firm level is the most important for pay negotiation rather than the industry/sectoral level which is used to set industry minimum levels, with anything above this negotiated at the firm level (see Broughton, 2009; European Commission, 2013).

3.2 Contract Types

There is a marked distinction between civil servants and other public sector employees in the majority of the countries that we study. For example, in France the status of *Fonctionnaire*, in Germany that of *Beamte* or of *Funcionarios* in Spain is very different to other public sector employment. The difference between being on a private labour law contract and a public law contract (civil servants) relates to protection from termination, wage schemes (as outlined above) and pension entitlements – which are generally better for civil servants (see below). The Netherlands is the exception to this, where the civil service does not enjoy the same sort of privilege as compared to the rest of the public sector and the private sector, does not have any greater employment protection, guaranteed career path or a separate pension scheme (see United Nations, 2006). With respect to contracts, one other notable outlier among our countries under study comes in Spain's use of fixed-term contracts, predominantly in the private sector. Throughout the period of our data, the proportion of employees on fixed-term contracts in Spain was approximately 30%. This is much higher than Italy (10%), Germany (12%) and both France and the Netherlands (14%) (see European Commission, 2004).

3.3 Entry Requirements and Career Progression

This distinction between employment in the public sector and employment in the subset of the public sector that is the civil service is seen also in recruitment and progression. For the most part, recruitment to the non-civil service roles is no different to recruitment into the private sector. Entry into the civil service is quite different however: in France, Italy and Spain, entry to the civil service is on the basis of open, competitive examinations held each year. Eligibility to sit the exam depends on educational qualifications and in some

[6]This is no longer the case in Germany where public pay is now set at regional level, but was the case during the period of our data.

cases (France) age. These countries recruit individuals explicitly for a career in the civil service and their suitability for such a career is assessed in the recruitment process. This is in contrast to Germany and the Netherlands where the recruitment system is appointment-based rather than career-based – suitability for the specific job rather than a full career is the assessment criterion. Moreover, unlike in France, Italy and Spain there are no entry examinations for the civil service in Germany or the Netherlands and there is no central recruitment administration – each ministry/department at the federal, state or local level recruits for the positions they have open. In theory all positions are open to anyone either within or outside the civil service with applicants hired on the basis of their suitability for the specific job in terms of their education, ability, previous experience and motivation.

For the most part, the countries in our data offer life-time tenure to their civil servants. This is the case in Germany, France, Italy and Spain: civil servants cannot be dismissed except for cases of misconduct and these terms apply regardless of whether the individual is employed at the national, regional or local authority level. The Netherlands differs in that civil servants do not have this degree of job security, instead having the same level of employment protection as other public and private sector workers.

As noted, Germany and the Netherlands differ from the other countries in that they recruit to the civil service for a particular position rather than for an entire career. Furthermore, in the Netherlands, there is no guaranteed and well-defined career path for a starting civil servant. Promotion is on the basis of merit, with no guaranteed wage increases on the basis of seniority. While this means that a full career in the civil service is not certain, it does allow for the rapid promotion of high-flyers within the service. Despite this lack of a guaranteed career, most civil servants in the Netherlands do remain in the service for their whole career, moving from post to post to advance through the hierarchical levels (see United Nations, 2006).

Germany is an intermediate case in which despite not being recruited with the full career in mind, civil servants follow well-defined career paths, as do non-civil servant public sector workers. There are four classes of public sector job and five grades within each. Movement up the grades is on the basis of seniority, and it is only at the very highest grade of civil servant that the pay is discretionary and not tied to experience. It is also worth noting that the German public sector increases pay for those who are married and have children – reflecting the "male bread-winner" model that dominates in the country.

France, Italy and Spain are very similar with respect to the pay and career structures in the public sector. Jobs are classified into groups, with the education level determining which group an individual will belong to and their starting pay and pay scale. Progress up the pay scale is then automatically determined on the basis of years served, though in each country there are mechanisms – bonus structures (France, Italy) and individual allowances (Spain) – that allow some element of merit-based pay and selection for promotion to higher levels. In addition to 'step progression' which is automatic with experience within a class, there is also 'class progression' which involves promotion to a new class of job, with a new pay scale, and may require the passing of a professional exam.

Thus in all countries, bar the Netherlands, the evolution of pay throughout a career in the public sector is very much determined by seniority, though with some flexibility around the basic systematic pay progression.

3.4 Pensions and Retirement

In many countries – including Germany, France, Italy and Spain – the pension schemes available in the public sector are seen as an important component of the total remuneration, and in the civil service in particular, part of the incentive to attract high skilled workers into this career. In contrast, in the Netherlands, there is not a distinctive scheme for the public sector in general or the civil service in particular, and no significant distinction between public sector and private sector pension provision in terms of contribution rates, funding arrangements or benefit structures. In the Netherlands each individual receives a flat-rate basic state pension from age 65, and this is supplemented by a quasi-mandatory occupational pension whether in the public or private sector. These components in theory guarantee everyone in the Netherlands a pension worth at least 70 percent of the net national minimum income, whichever sector they have been employed in (see Palacios and Whitehouse, 2006). This reflects another difference between the Netherlands and the other countries under consideration: the Dutch national pension system has always been based on the Beveridge model, in which prevention of poverty in old age is the primary objective of the system. In contrast, the systems in Germany, France, Italy and Spain derive from the Bismarckian model which is more employment-centric, with maintenance of social status into retirement the objective, over and above simple poverty prevention (see Eich, 2009; Hinrichs, 2000).

In Germany there are different pension schemes available to workers broken down into three categories: civil servants, other public sector workers and private sector workers. Civil servants do not pay national insurance contributions in the way that other public and private workers do, rather they pay directly into their separate pension scheme. Their pensions are defined benefits, with the value depending on years of service, seniority and final pay. This special pension arrangement is codified in law, with changes to the value of the entitlements having to be made via legislation, in response to changing political and budgetary circumstances. In contrast to other workers, civil service pensions are also taxed. These pension arrangements do not extend to cover other employees in the public sector who instead contribute to the statutory social security pension scheme and are entitled to the earnings-related pension and an occupational pension instead. This is similar for the private sector workers - they pay into the national social security system and are entitled to an earnings related pension, supplemented by an occupational pension. However, while in the public sector (non-civil service) these occupational pensions are quasi-mandatory as part of national pay agreements, in the private sector coverage is much less, meaning that the public sector pension arrangements are generally more favourable than the private sector - much more in the case of civil servants (see Börsch-Supan and Wilke, 2004).

In France, the civil servant scheme is separate with the pension value calculated depending on the age at retirement, marital status, the grade-related pay at the point of retirement or the number of years worked and the nature of the job at retirement. The theoretical maximum value of the pension is 75 per cent of the final pay and could be achieved after 38 years of service. The scheme available in the private sector comprises a basic state earnings related pillar, a mandatory occupational pension plus the option of voluntary additional personal schemes. Between them this allows for a replacement rate of around 71 percent and for low income workers the pension should equate to no less than 85 percent of the national minimum wage income (see Eich, 2009).

The main state private sector scheme in Spain (the RGSS) requires 15 years of contributions plus complete withdrawal from the labour force. At this point the pension is worth 60 percent of the benefit base. Additional years increase this replacement rate up to the point where at 35 years of contributions the pension is worth 100 percent of the base. The base is calculated as a moving average of the previous 15 years earnings (eight before reforms in 1997) prior to retirement. Retirement before age 65 is possible but with large penalties (7% reduction in replacement rate per year before age 65). For those who contribute the full 35 years or close to that, the scheme is therefore extremely generous (see Boldrin et al, 1999). Unlike Germany and France, the Spanish scheme for civil servants is the same as for all public sector workers, is funded by social security contributions and is not particularly more advantageous than the main state scheme open to private sector workers. There are benefits for public employees - they can continue to work part-time whilst drawing their pension - yet the generosity of the main private scheme makes the civil service pension less of a specific attraction.

Italy is slightly different: its standard state pensions are related to earnings (and therefore contributions) over the entire working life and to age at retirement. Individuals can choose a retirement age between 57 and 65, with pensions then related to the average life expectancy at the age of retirement via a conversion coefficient calculated on the basis of an actuarial discount. The coefficients, which make the present value of future benefits equal to capitalized contributions, can be revised every ten years on the basis of changes in life expectancy and the rate of growth of GDP and earnings. In contrast to elsewhere, the minimum number of contribution years in order to be entitled to a pension is just five. Any individual who has accumulated 35 years of contributions is entitled to retire at that point (whatever their age) and start drawing a seniority pension. Prior to 1992 the public sector pensions were much more favourable, with seniority pensions being able to be drawn with much fewer than 35 years of service (just 20 for public sector workers), however for the period of our data the 35 years rule was common to both sectors. The public sector scheme does remain advantageous, allowing a replacement rate of up to 80 percent whereas the private scheme equivalent maximum is closer to 70 (see Franco, 2002).

With respect to age at retirement, the normal retirement age in each country does not differ between the sectors, with the exception of Spain where public sector workers have a mandatory retirement age of 65 (which is the normal retirement age in the private sector) but it is normal to retire at 60 especially if 35 years of service have been accrued (the incentive to continue working after that point is weak as pension values increase very little after 35 years of service have been reached, see Palacios and Whitehouse, 2006).

4 Data

4.1 The European Community Household Panel

We use data from the European Community Household Panel (henceforth ECHP) which is a longitudinal survey of households and individuals carried out in 15 European Union countries annually between 1994 and 2001. Within each country, we restrict our sample to males in order to avoid issues around female labour market participation and we also drop from the sample anyone who is retired. We exclude individuals who have never entered the labour market i.e. young men who are yet to leave full-time education. Among those who are working we restrict the sample to full-time[7] workers (defined as working 30+ hours per week) and only include the observations for individuals aged from 20 to 55 in their first observation. We define three 'sectors' of labour market activity: employment in the private sector, employment in the public sector, and unemployment.[8] We use current gross monthly earnings reported once per year and deflated using

[7]There are slight systematic differences in part-time shares across sectors but the percentage of employees working part-time in each dataset is extremely small: for the private sector (resp. public sector) the figures are Germany 0.5% (1.0%), Netherlands 2.8% (4.5%), France 1.5% (3.7%), Italy 1.5% (3.2%), Spain 1.9% (1.6%). Including/excluding part-time workers in the analysis has negligible impact on our results.

[8]In addition to those reporting themselves to be unemployed, the unemployment category includes: working unpaid in a family enterprise, in education or training (though having been in the labour market at some point), doing housework, looking

each country's CPI and detrended within each country. We trim the earnings data by treating earnings observations below the 2nd and above the 98th percentile of earnings within each 'education'×'job sector' cell as missing data.[9]

The rules governing inclusion in the sample, added to the relatively small population size of some of the countries involved in the ECHP, results in sample sizes that are too small to implement our model in Belgium, Luxembourg, Denmark, Greece, Ireland, Austria, Finland, Portugal and Sweden. However, we do retain a usable sample in five countries: Germany, the Netherlands, France, Italy and Spain.[10]

4.2 Basic Sample Description

In each country, the constructed sample retains the men who satisfy the sample selection criteria outlined above and have a minimum of 4 (maximum of 8) consecutive observations.[11] Table 1 shows for each dataset the number of individuals in total, the average number of consecutive observations per individual, and then this information broken down according to the sector in which the individual is first observed.

The mean number of consecutive observations per individual is around 6.5 and does not exhibit much variation across countries or sectors of employment in the first observation. Individuals initially observed unemployed have a slightly smaller (6) average number of sample observations.

For each country we look at (log) current gross monthly earnings. Differences in the distribution of monthly work hours for full-time workers could lead to differences between the picture we will describe and that obtained with hourly wages. As our focus is to construct a measure of lifetime differences in the value of employment in either sector, we have chosen to use monthly earnings. Table 2 shows the weekly hours distributions by sector for each country. In France and Spain, median weekly hours are identical across the two sectors. In Germany, the Netherlands and Italy, the public sector median weekly hours are respectively 1, 2 and 4 hours less than private sector hours. The standard deviation of hours tends to be smaller in the public sector, the difference ranging from 57 minutes (Italy) to 1 hour and 40 minutes (Netherlands).

after children or other persons, working less than full-time hours, and other economically inactive people. We include these categories of inactivity in the unemployment definition in order not to lose the information of individuals who temporarily transit out of the labour market, however any individual who has more than three periods of inactivity or more than two consecutive periods of inactivity is dropped. Any individual working less than full-time hours has their earnings information censored and so does not contribute to the modelling of wages.

[9] We do not drop these *observations* only replace their earnings as missing. Therefore the individuals concerned still convey information to the sample and contribute to the modelling of the labour market dynamics.

[10] Results using the UK sample in the ECHP, which is itself taken from the BHPS, concur with those found by Postel-Vinay and Turon (2007) when using a larger sample available in the British Household Panel Survey.

[11] There is some sample attrition which we assume to be exogenous. Some of the attrition is a consequence of our sample construction rules that treat individuals as censored from the first time they have a gap in their response history. See Appendix A for more details.

4.3 Differences in Education

The ECHP includes a standardised education measure – the ISCED classification[12] – coded into 3 categories: "high" is ISCED levels 5-7 and corresponds to all classes of tertiary level education, "medium" is ISCED level 3, corresponding to upper-secondary (post-compulsory) education, and "low" is ISCED levels 0-2, corresponding to levels of education up to the end of secondary schooling.

Table 3 shows that Germany, the Netherlands and France have similar proportions of highly educated workers (around 25% of the workforce) while just under one third of the Spanish workforce falls in the high education bracket and only 10.5% in Italy. Proportions of low-educated workers vary considerably across countries, from a low 10.5% in Germany to 43.3% in Spain. In each country, the public sector has a greater proportion of highly educated workers. This is particularly pronounced in Spain where the public sector proportion of highly educated is more than double the corresponding figure for the private sector. Public sector employees are everywhere older and with greater potential labour market experience[13] than their private sector counterparts. This gap is most marked in the Netherlands and Italy (2.6 and 2.0 years of experience, respectively).

4.4 Raw Differences

As Table 4 illustrates, the raw public pay gap in wage levels is positive in all five countries, from a few log-points in Germany, the Netherlands and Italy (4.9, 9.3 and 10.2 respectively) to 13.4 log-points in France (14.3%) and 27.0 log points (31.0%) in Spain. With respect to the dispersion of earnings the public and private sectors exhibit notable differences. For Germany, the Netherlands, France and Spain, the standard deviation of log earnings is lower in the public than the private sector to around the same extent. In Italy the extent of pay dispersion is similar in each sector.

Our point in this paper is that these differences only represent one dimension of public-private differences as we will show below that dynamic differences in earnings mobility and job mobility are substantial too and must be taken into account if one tries to gauge long-term differences between employment in either sector.

One-lag autocovariances of earnings show a greater persistence amongst those individuals continuously employed in the public sector than amongst those continuously employed in the private sector, across all countries.

As can be seen from the 'Observed' panels of Tables 16–20 direct transitions from the private to the

[12] International Standard Classification of Education. We discuss in Appendix B an alternative measure of education.

[13] 'Labour market experience' or more accurately '*potential* labour market experience' is defined as current age minus the age when the individual first entered the labour market.

public sector are very uncommon: only 1% to 2% of individuals initially employed in the private sector move to the public sector the next year; however movements in the opposite direction are more frequent, between 7.0% and 8.5% of those employed in the public sector in year *t-1* are employed in the private sector in year t, with the exception of France where transition probablities relating to both directions of movement are very small. Moreover, for each country bar the Netherlands, the annual transition rate into unemployment from the private sector is much larger than the corresponding figure for the public sector.

The descriptive statistics shown in this section make it clear that in all countries, the public and private sectors differ in cross-sectional earnings levels and both earnings and employment dynamics – all elements that will be important to forward-looking agents.

5 A Model of Employment and Wage Dynamics, Between and Within Sectors

5.1 General Structure

Our statistical model follows Postel-Vinay and Turon (2007), adjusted to accommodate the format of ECHP data. In each country, the constructed dataset is a set of N individuals, indexed $i = 1, \dots N$, each of whom we follow for T_i consecutive years (where $4 \leq T_i \leq 8$, for all i). Each year we observe the individual's employment status and sector, their monthly earnings if employed and a selection of characteristics. A typical observation for an individual i can be represented by the vector[14] $\mathbf{x}_i = \left(\mathbf{y}_i, \mathbf{S}_i, \mathbf{z}_i^v, z_i^f\right)$, where:

- $\mathbf{y}_i = (y_{i1}, \dots, y_{iT_i})$ is the observed sequence of individual i's log earnings flows.
- $\mathbf{S}_i = (S_{i1}, \dots, S_{iT_i})$ is the observed sequence of individual i's labour market states at interview dates. We define the three distinct labour market states: employed in the private sector, employed in the public sector and unemployed. S_{it} indicates which of the three above states individual i is in at date t.
- $\mathbf{z}_i^v = \left(z_{i1}^v, \dots, z_{iT_i}^v\right)$ is a sequence of time-varying individual characteristics. In our application we only consider (polynomials in) potential labour market experience, defined as the current date less the date at which individual i left full-time education.
- Finally, z_i^f is a set of individual fixed characteristics. It includes education level (the 3 ISCED levels) and experience at the time when the individual entered the panel. Hence $\mathbf{z}_i^v$ is deterministic conditional on z_i^f.

[14]Throughout the paper vectors will be denoted by boldface characters.

In addition to the individual observed heterogeneity as captured by $\mathbf{z}_i^v$ and z_i^f, we allow time-invariant unobserved heterogeneity to influence individual's wages and selection into the various labour market states. The specific form we allow this heterogeneity to take is outlined in section 5.2 below, for now we simply append the set k_i of time-invariant unobserved characteristics to the individual's data vector $\mathbf{x}_i$.

We aim to estimate simultaneously transitions between unemployment and employment, transitions between the public and private sector, and earnings trajectories within and between employment sectors. Omitting the parameters that condition the various parts of the model for the sake of conciseness, we define the individual's contributions to the complete likelihood as:

$$\mathcal{L}_i\left(\mathbf{x}_i, k_i\right) = \ell_i\left(\mathbf{y}_i \mid \mathbf{S}_i, \mathbf{z}_i^v, z_i^f, k_i\right) \cdot \ell_i\left(\mathbf{S}_i \mid \mathbf{z}_i^v, z_i^f, k_i\right) \cdot \ell_i\left(k_i \mid z_i^f\right) \cdot \ell\left(z_i^f\right). \tag{1}$$

This individual likelihood contribution comprises four terms. The last term, $\ell\left(z_i^f\right)$, is the observed sample distribution of individual characteristics z_i^f. Since $\mathbf{z}_i^v$ is deterministic conditional on z_i^f there is no need for it to feature in this last term. This sample distribution is observed and is independent of any parameter. The penultimate term, $\ell\left(k_i \mid z_i^f\right)$, is the distribution of the unobserved individual heterogeneity k_i given observed characteristics z_i^f. The second term is the likelihood of an individual's labour market history given individual heterogeneity, $\ell\left(\mathbf{S}_i \mid \mathbf{z}_i^v, z_i^f, k_i\right)$. Finally the first term in the individual likelihood contribution is the likelihood of earnings history given their labour market history and individual heterogeneity, $\ell\left(\mathbf{y}_i \mid \mathbf{S}_i, \mathbf{z}_i^v, z_i^f, k_i\right)$. The first three terms in the individual likelihood depend on various subsets of the model's parameters. We obtain estimates of those parameters by maximizing the sample log-likelihood, $\sum_{i=1}^N \log\left[\int \mathcal{L}_i\left(\mathbf{x}_i, k_i\right) dk_i\right]$. We will now outline the specifics of the modelling of each component of (1), beginning with the treatment of unobserved individual heterogeneity.

5.2 Unobserved Heterogeneity

In addition to the observed heterogeneity, we consider two types of unobserved heterogeneity: $k_i = (k_i^m, k_i^y)$. The first dimension of this heterogeneity, k_i^m, relates to the individual's propensity to be unemployed or to work in the public sector (and will be referred to henceforth as their 'mobility class'). The second dimension, k_i^y, refers to heterogeneity in terms of earnings (hereafter referred to as 'wage class') through its impact on both earnings levels and earnings mobility. Both k_i^m and k_i^y are time-invariant random effects which are allowed to be correlated in an arbitrary manner. The mobility class, k_i^m, conditions all the parameters of the model relating to employment and sector history, while the wage class, k_i^y, conditions the parameters relating to earnings history both in terms of levels and persistence. Allowing for different unobserved mobility classes leaves room for some people to have a higher propensity to work in the public sector (or to be unemployed), addressing the selection problem outlined in section 4. Moreover, the inclusion of earnings heterogeneity via a time-invariant wage class term helps to capture the persistence in earnings rank, which is not always possible to characterise with fairly low-order Markov processes. We refer to mobility and wage *classes* as we employ a finite mixture approach to modelling the unobserved heterogeneity in which each individual can belong to one of K^m mobility classes and K^y wage classes.[15] In total there are $K = K^m \times K^y$ classes. The probability of belonging to a given class depends on the observed individual heterogeneity, z_i^f:

$$\Pr\left\{k_i^m, k_i^y \mid z_i^f\right\} = \Pr\left\{k_i^y \mid k_i^m, z_i^f\right\} \cdot \Pr\left\{k_i^m \mid z_i^f\right\}. \tag{2}$$

To be more specific, we model each component of (2) as a multinomial logit with K^y and K^m outcomes respectively. All of the details of the model specification are gathered in Appendix E.

5.3 Labour Market Mobility

The second component of $\mathcal{L}_i(\mathbf{x}_i, k_i)$ in (1) relates to the individual's labour market mobility. The transitions between the three labour market states are specified as to depend only on the individual's state in the previous observation and on observed and unobserved characteristics, thus labour market states are modelled as following a conditional first-order Markov chain. It is useful at this point to introduce the indicators e_{it} and pub_{it} which respectively denote the individual's employment state and job sector at the date-t interview. Specifically, $e_{it} = 1$ if i is employed at the date-t interview, 0 if unemployed; pub_{it} is only defined if $e_{it} = 1$, with $\text{pub}_{it} = 1$ if individual i is employed in the public sector, and 0 if he is employed in the private sector. We thus model the complete (within panel) labour market histories in two stages: the probability of employment at the date-t interview ($e_{it} = 1$), given last period sector and individual heterogeneity, and the probability of public sector employment at the date-t interview ($\text{pub}_{it} = 1$), given employment at date-t ($e_{it} = 1$), previous sector and individual heterogeneity. These probabilities are specified as:

$$\begin{aligned}\Pr\left\{e_{it}, \text{pub}_{it} \mid S_{i,t-1}, z_{i,t-1}^v, z_i^f, k_i^m\right\} = \Pr\left\{e_{it} \mid S_{i,t-1}, z_{i,t-1}^v, z_i^f, k_i^m\right\} \\ \times \left[\Pr\left\{\text{pub}_{it} \mid e_{it}, S_{i,t-1}, z_{i,t-1}^v, z_i^f, k_i^m\right\}\right]^{e_{it}},\end{aligned} \tag{3}$$

where $S_{i,t} = (e_{it}, \text{pub}_{it})$. Both elements of (3) are modelled as logits.

We address our initial conditions problem by specifying the distribution of the initial labour market state, S_{i1}, i.e. model the joint probability of $(e_{i1}, \text{pub}_{i1})$ as a function of observed and unobserved heterogeneity

[15] We implement this approach following Postel-Vinay and Turon (2007), the finite mixture approach providing a tractable method to account for unobserved heterogeneity.

$\left(z_i^f, k_i^m\right)$ in the form of a product of two conditional logits:

$$\Pr\left\{e_{i1}, \text{pub}_{i1} \mid z_i^f, k_i^m\right\} = \Pr\left\{e_{i1} \mid z_i^f, k_i^m\right\} \cdot \left[\Pr\left\{\text{pub}_{i1} \mid z_i^f, k_i^m\right\}\right]^{e_{it}}. \tag{4}$$

Therefore, the contribution to the likelihood of an individual's job mobility trajectory is:

$$\ell_i\left(\mathbf{S}_i \mid \mathbf{z}_i^v, z_i^f, k_i^m\right) = \Pr\left\{S_{i1} \mid z_i^f, k_i^m\right\} \times \prod_{t=2}^{T_i} \Pr\left\{S_{it} \mid S_{i,t-1}, z_{i,t-1}^v, z_i^f, k_i^m\right\}, \tag{5}$$

where the components of the latter product are given by (3).

5.4 Earnings Process

The first term in $\mathcal{L}_i(\mathbf{x}_i, k_i)$ (equation (1)) involves the modelling of individual earnings trajectories. We only have earnings information for individuals who are observed in employment, which means that earnings information is censored for periods in which an individual is unemployed. We assume log earnings trajectories $\mathbf{y}_i$ to be the realisation of a Markov process of continuous random variables Y_t. Given the limitation of the sample dimensions, both in terms of N and T, a second-order Markov process combined with our assumed unobserved heterogeneity specification seems the best option. This allows us to write the likelihood of a given earnings trajectory over T periods as a product of bi- or tri-variate densities:

$$\ell(\mathbf{y}) = \ell(y_2, y_1) \cdot \prod_{t=3}^{T} \ell(y_t \mid y_{t-1}, y_{t-2}) = \ell(y_2, y_1) \cdot \prod_{t=3}^{T} \frac{\ell(y_t, y_{t-1}, y_{t-2})}{\ell(y_{t-1}, y_{t-2})}. \tag{6}$$

Again, so as not to overload the equations, we temporarily omit the conditioning variables and individual index.

We assume that marginal log-earnings distributions to be normal conditional on observed and unobserved individual heterogeneity. Thus both the earnings mean and variance are allowed to depend on both observed and unobserved heterogeneity as well as current sector and previous labour market status:

$$\begin{aligned} y_{it} \mid \text{pub}_{it}, e_{i,t-1}, z_{it}^v, z_i^f, k_i^y \quad &\sim \quad \mathcal{N}(\mu_{it}, \sigma_{it}^2) \\ \text{with } \mu_{it} = \mu\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right) \quad &\text{and} \quad \sigma_{it} = \sigma\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right). \end{aligned} \tag{7}$$

Introducing normalised log-earnings as $\widetilde{y}_{it} = \frac{y_{it} - \mu_{it}}{\sigma_{it}}$, we now have the triple $(\widetilde{y}_{it}, \widetilde{y}_{i,t-1}, \widetilde{y}_{i,t-2})$ and the pair $(\widetilde{y}_{it}, \widetilde{y}_{i,t-1})$ as Gaussian vectors with covariance matrices $\underline{T}_{it}^{(3)}$ and $\underline{T}_{it}^{(2)}$ respectively, which we expand as:

$$\underline{T}_{it}^{(3)} = \begin{pmatrix} 1 & \tau_{i,t,t-1} & \tau_{i,t,t-2} \\ \tau_{i,t,t-1} & 1 & \tau_{i,t-1,t-2} \\ \tau_{i,t,t-2} & \tau_{i,t-1,t-2} & 1 \end{pmatrix} \quad \text{and} \quad \underline{T}_{it}^{(2)} = \begin{pmatrix} 1 & \tau_{i,t,t-1} \\ \tau_{i,t,t-1} & 1 \end{pmatrix}. \tag{8}$$

These τs are individual-specific and are allowed to vary with observed and unobserved heterogeneity and with labour market sector at t, $t-1$ and $t-2$:

$$\begin{aligned} \tau_{i,t,t-1} &= \tau_1\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right) \\ \text{and} \quad \tau_{i,t,t-2} &= \tau_2\left(\text{pub}_{it}, \text{pub}_{i,t-1}, \text{pub}_{i,t-2}, z_{it}^v, z_i^f, k_i^y\right). \end{aligned} \tag{9}$$

$\mu(\cdot)$, $\sigma(\cdot)$, $\tau_1(\cdot)$ and $\tau_2(\cdot)$ are functions specified in Appendix E.

For individuals with complete earnings information, the equation (6) earnings trajectory simplifies to:[16]

$$\ell_i\left(\mathbf{y}_i \mid \mathbf{e}_i, \mathbf{pub}_i, \mathbf{z}_i^v, z_i^f, k_i^y\right) = \left[\prod_{t=1}^{T} \frac{1}{\sigma_{it}}\right] \times \left[\frac{\prod_{t=3}^{T} \varphi_3\left(\widetilde{y}_{it}, \widetilde{y}_{i,t-1}, \widetilde{y}_{i,t-2}; \underline{\tau}_{it}^{(3)}\right)}{\prod_{t=3}^{T-1} \varphi_2\left(\widetilde{y}_{it}, \widetilde{y}_{i,t-1}; \underline{\tau}_{it}^{(2)}\right)}\right], \tag{10}$$

where $\varphi_n\left(\cdot; \underline{\tau}^{(n)}\right)$ is the n-variate normal pdf with mean 0 and covariance matrix $\underline{\tau}^{(n)}$.

We are effectively assuming that normalised log earnings follow a familiar AR(2) process, though we build in some flexibility by allowing the τs to depend on observed (and unobserved) individual characteristics in (9). This has the dual appeal of (a) helping to more accurately fit the observed mobility of income ranks, and (b) informing one of the key questions that we aim to address: namely how income mobility varies across individuals and across sectors. The τs offer an index of income mobility which we will use to shed light on this key question. We acknowledge that an implicit assumption of the model outlined above is that transitory shocks to the earnings process are independent of the transitory shocks to the processes determining mobility between the labour market sectors. To put this another way, we assume that the individual earnings process only affects individual mobility between states through either observed characteristics (e.g. education and experience) or through the time-invariant unobserved individual random effects k_i^m and k_i^y, and not through any transitory (unobserved) shocks. This assumption leads to the separability of the likelihood function into a part relating to labour market mobility and a separate part relating to the earnings process.

Although this assumption may appear unrealistic with regard to job mobility motivated by wage differences, our aim in this paper is to present a purely descriptive picture of employment and earnings in the private and public sectors in terms of relating average (over the wage distribution) mobility between sectors, and earnings levels and dynamics in each sector. The stylised facts presented here will need to be understood within a structural model highlighting the mechanisms of individual behaviour giving rise to these facts. This is what we aim to do in another paper (see Bradley, Postel-Vinay and Turon, 2013), where individuals earning relatively little in either sector do have a relatively strong incentive to accept outside offers from either the same or the other sector, so that worker mobility is related to wage rank.

[16] For the derivation of this expression see Appendix E. For individuals with incomplete earnings information, the above expression is amended to accommodate for missing data, again see Appendix E for details.

5.5 Likelihood Maximisation

Having established the specifications for the individual contributions to the complete likelihood, $\mathcal{L}_i(\mathbf{x}_i, k_i)$ defined above, the parameter estimates are obtained by maximisation of the sample log-likelihood:

$$\sum_{i=1}^{N} \log \left(\sum_{k_i^m=1}^{K^m} \sum_{k_i^y=1}^{K^y} \mathcal{L}_i \left[\mathbf{x}_i, (k_i^m, k_i^y) \right] \right), \tag{11}$$

where as touched on above, the individual random effects $k_i = (k_i^m, k_i^y)$ are integrated out of the complete likelihood (1). We proceed by employing a sequential (two-step) version of the EM algorithm (described in Appendix F) which takes advantage of the separability of (1) to estimate the parameters governing the mobility process between labour market states by running a first EM procedure, before estimating the parameters governing earnings processes in a second EM procedure, in which the job mobility parameters are given their first-step estimated values. The advantage of this procedure is that it is computationally more stable given arbitrary starting values and is more tractable than a direct frontal maximisation of the total sample likelihood (11). Furthermore, it can be shown that under the assumptions of identification of the model parameters and numerical convergence of the algorithm, that the two stage approach converges to a consistent estimator of the parameters (see Bonhomme and Robin, 2009).[17]

6 Results

We now turn to the presentation of our results in the following three steps. We first examine the estimated distribution of unobserved heterogeneity in each country, both in terms of mobility and income and show that allowing for unobserved heterogeneity matters both for the prediction of individual employment (and sectoral) trajectories and for income levels and dynamics. We then examine the fit of the model for each country, in order to establish that the model does a good job of replicating not only cross-sectional earnings statistics in each country, but also the dynamics of the labour market and earnings. In the third and final stage, we summarise our results for the five countries in our sample (and the UK for comparison) along the five dimensions of public-private differences highlighted above, namely: cross-sectional incomes (mean and dispersion), income persistence, returns to experience, and job loss rate. Our estimation allows us to predict these differences for the whole sample (by estimating a counterfactual for each individual in the sample) as well as differences across sectors including the difference in the subsets of our sample that have selected themselves in each sector of (un)employment.

[17]It does have the drawback in that it converges to an estimator which differs from the maximum-likelihood estimator and is not efficient, being a two-step, incomplete-information procedure.

Two striking features emerge from our results. First, public-private differences observed and commented upon in the public debate are in most cases largely the result of individual selection into sectors. Second, we find sizable differences between sectors in all five of the dimensions that we examine, suggesting that the usual emphasis on cross-sectional earnings and job security differences gives an incomplete picture of the public premium by ignoring differences in income dynamics.

6.1 *Unobserved heterogeneity*

The model is estimated under the assumption that, within each country, individual unobserved heterogeneity can be modelled with two or three mobility classes and two wage classes. We set the number of mobility classes to three for all countries except the Netherlands and France, where it is set to two. We were guided in the choice of these numbers by pragmatism, trying to balance the various concerns of descriptive accuracy, computational tractability and model fit.[18] Rather than commenting on five countries times up to 76 coefficients directly, we choose to concentrate on more easily interpreted statistics – such as the predicted differences in the four dimensions of interest, with and without controlling for selection. (Full tables of coefficient estimates and standard errors are reported in Appendix G.[19]) This subsection will however include some details of the results with respect to the two types of unobserved heterogeneity – mobility and earnings – embedded in our specification.

Tables 5 to 10 describe the distribution of individual types among the various unobserved heterogeneity classes as well as the composition of each class in terms of education and experience.[20] The first thing to note in Table 5 is that there is a substantial proportion of individuals in each class within each country, which supports the need to allow for this type of heterogeneity given the observable characteristics available in our dataset. With regard to the joint distribution of unobserved heterogeneity classes, all classes (bar one in Germany) are populated by at least 5% of the sample in each country. In the model specification, no restriction is imposed on the correlation betweeen the two dimensions of unobserved heterogeneity, and we do find a varying degree of association between the probabilities of an individual to belong to a given

[18]On one hand, reducing the number of income classes does not replicate the income persistence observed in the data. An alternative way to increase model persistence would be to increase the order of the Markov process but the limited length of our panel precludes this possibility. On the other hand, increasing the number of classes increases the computational cost dramatically and makes the exposition more cumbersome when referring to different types. Usual information criteria would tend to suggest more classes but Nylund et al. (2007) suggest that these can be sensitive to small sample sizes.

[19]An additional caveat should be raised here. Standard errors are calculated using the product of scores, which is consistent if the parameter values used are ML estimates. Because, as mentioned earlier, our EM-based procedure is sequential, it differs from the ML estimator. Thus, to attain consistent estimates of the standard errors we bootstrapped the entire model. Standard errors on public premia and sector specific quantities are reported in the main results tables, standard errors for all of the underlying model's coefficients are reported in Appendix G.

[20]Note: the figures in Tables 6 to 10 refer to the first observation for each individual, in order that they are not affected by attrition. As a result, mean experience is lower than reported in Table 3 which uses the full NxT datasets, and some mobility classes have zero representation in the public sector, however this is due to looking only at the initial observation, all class types are represented in each sector for at least some of the time in the full panel data.

mobility class and a given wage class across countries.

The pattern of the distribution across classes is very much correlated with selection into labour market state. When three mobility classes are used we find one type selecting overwhelmingly into the private sector, one into the public sector, while the third class is a mixture of mainly private sector workers, though with a higher unemployment rate than the other two. Note however that there is enough sectoral movement for each type of worker to allow for our model coefficients to be identified.[21] In the remainder of the paper we will designate the mobility class which selects itself predominantly in the private sector (resp. public sector) the 'private worker' (resp. 'public worker') class and the class with a higher tendency to be unemployed the 'high unemployment' class.

The upper panels of Tables 6 to 10 show the human capital characteristics of each mobility type. Compared to the 'private worker' type, the 'public worker' type have a higher proportion of highly educated workers and slightly more experience. The 'high unemployment' type have substantially lower education than the other two types. With respect to the distribution across income types, each of the 5 countries' sample is fairly evenly split between the two earnings classes, with one class earning more on average than the other, in both sectors and often (i.e. in most countries) enjoying greater returns to experience. Figures 6 to 10 in section 11.4 illustrate the earnings mean and returns to experience for the total sample and for each wage class. These visually confirm the numbers from the bottom panels of Tables 6 to 10 showing that one class usually earns more than the other and that this holds true in both sectors. Again, the 'higher earner' types tend to be more educated than the other type, as is also illustrated in the bottom panels of Tables 6 to 10.

6.2 *Model Fit*

In order to assess the model fit, we simulate the model in each country and then compare the model-generated data outcomes with the real data. To achieve this, within each country, we replicate our panel as many times as there are unobserved heterogeneity classes in total so that we have one set of observations per person per unobserved heterogeneity class. We use the estimated job mobility and earnings processes to simulate individual labour market and earnings trajectories for each (individual$\times$class) in the sample. We then produce simulated descriptive statistics, weighting each $\{\text{individual } i, \text{class } (k^m, k^y)\}$ observation by the probability that individual i belongs to mobility class k^m and wage class k^y, given individual's observed characteristics $\mathbf{x}_i$: $\Pr\{k_i^m = k^m, k_i^y = k^y \mid \mathbf{x}_i\}$.

[21]See Appendix C for figures on transition matrices by class.

6.2.1 *Worker Allocation and Mobility Between States*

Looking at the cross-sectional statistics for all countries, Tables 11 to 15, it seems that the model fits the observed pattern of worker allocation to states – private sector employment, public sector employment and unemployment – very well indeed. Moreover, Tables 16 to 20 illustrate the observed and simulated cross-job-state transition matrices for each of the countries at intervals of one and five years.[22] Looking at the upper panel of each table, we can see that transitions from $t-1$ to t are generally fitted very well, in all cases the maximum absolute distance between the observed rate and the model-predicted rate being less than 8%-points and in most cases much less than that. In addition to the maximum distance between the observed and predicted figures in any of the nine entries in each 3×3 matrix, we report the maximum absolute distance between the observed and predicted figures relating to the 2×2 matrices formed by excluding the unemployment column and row of each matrix. This shows how well the model is fitting persistence in sector for those employed, and the movement between sectors. In each case, for the $t-1$ to t transitions, we fit these 2×2 matrices very well, the error being of the order of 1% to 1.5%-points. This shows that we are fitting the employment sector persistence well in all countries; the prediction errors are due to an under-prediction of unemployment persistence to a greater (Germany, Netherlands, Spain) or lesser (France, Italy) extent. Specifically, we under predict the unemployment persistence because we are over-predicting the rate of re-employment into the private sector – the rate of re-employment into the public sector is fitted well in each country.

Looking at the longer-lag transitions, from $t-5$ to t, it is clear that the under-prediction of unemployment persistence continues to be a problem in the Netherlands and now also in France. In the other countries the maximum distance between predicted and observed figures is in the region of 10%-points. We note however that the 2×2 matrices distances continue to be small, of the order of 5%-points, indicating that we are fitting the persistence in and movement between sectors for employees pretty well. In sum, these tables indicate that the statistical model does a good job in all countries of fitting the observed transitions between the labour market states, both at short and longer lags.

6.2.2 *Earnings Dispersion and Earnings Mobility*

We now turn to the model fit in terms of cross-sectional earnings distribution and earnings persistence – across the whole earnings distribution. Concentrating initially on the former, Figures 1 to 5 plot the observed

[22] With up to 8 observations for some individuals in each dataset, in theory we could look at 7-year lags for each country, however as there are relatively small numbers of individuals who have 8 observations, the cell sizes in the predicted data preclude robust observed matrices at longer than 5 lags.

and predicted log earnings densities for the whole sample and for the private and public sectors separately. These figures also include the wage class-specific densities, in each case normalised at the relative size of each class within each sector. In each country the model fits the observed wage distribution well. This suggests that the mixture of two normal densities in each country is enough to give a good fit of the observed wage density in each country.

For the purposes of our analysis, it is important not only to fit the cross sectional distributions of earnings well but also the mobility of earnings. We simulate full individual labour market histories – i.e. featuring both earnings *and* job state transitions – with earnings evolving according to the process outlined in our specification. We can therefore compare the predicted earnings quintile transition matrices with those obtained from the real data. Again we do this at lags of both one and five years, see Tables 21 to 25.

Concentrating firstly on the 1-period transition matrices (upper panel of each table), across all countries and cells of the matrices, the discrepancy ranges from 5 to 10%-points. Given the relatively parsimonious specification of earnings means, variances and covariances, and that we have only four to six unobserved heterogeneity classes in total, this is a very good fit. Moreover, as we move to longer lags, (lower panel of each table), though there is an increase across the board in the maximum absolute distance between the observed and predicted figures, the increases are not large for most of the countries, with maximum distances ranging from 7 to 14% points. Spain is an exception to this. The five-lag maximum distance of 18% suggests that the model does less well at fitting earnings mobility in this country, though arguably it still is a satisfactory fit.

Taking into consideration the fit of cross-sectional job sector, job sector mobility, the cross-sectional earnings distribution and earnings mobility for each country we have seen that our statistical model does a good job of capturing the observed levels and dynamics of labour market state and individual income in each country and supports the specification chosen. This choice of specification involved balancing competing criteria and was constrained by the wish to estimate a common model for all countries.

6.2.3 *Possible Alternative Specifications*

It is clear from the observed data that earnings are highly persistent in each country, and the assumptions of our model give two mechanisms through which this persistence is captured: the 2^{nd}-order Markov process for the evolution of earnings, and the time-invariant unobserved wage classes. The combination of these assumptions goes a long way to capturing the observed persistence in each country. However, if we look at the prediction errors for each country, in Tables 21 to 25, we see that for both the one-period earnings transitions and the five-period transitions, the model in general *under*-predicts the persistence in earnings. For some countries, persistence in the lowest quintile(s) of earnings is actually over-predicted, especially at the longer time lag, however the majority of cells in the main diagonal of each country's income quintile transition matrices are under-predicted by the model – indicating that we *over*-predict earnings mobility to some extent in each country. This aspect of the model could potentially be improved by altering the two assumptions relating to the earnings process, either by increasing the order of the Markov earnings process or by increasing the number of latent earnings heterogeneity classes. However, given the nature of our estimation procedure, the computational cost of expanding the model in either of these directions is very high. There is a trade-off between the amount of "built-in" persistence resulting from the order of the Markov process, and the additional earnings auto-correlation introduced by the time-invariant unobserved earnings classes. The choice we made of a 2^{nd}-order Markov process with two wage classes was guided, as ever, by a number of competing concerns including computational tractability, parsimony, model fit and the aim to estimate the same model specification for each country. Given these concerns, the model specification was guided by the $N \times T$ dimensions of each of the datasets we have: in each country we have a relatively small N dimension – between 2564 (Netherlands) and 4567 (Italy) individuals – balanced by a longer T dimension – each individual having at least 4 and up to 8 observations.

There are a number of possible alternative strategies that are computationally tractable. For example, removing the unobserved earnings classes altogether would provide a model that is computationally quick and easy to estimate, however in testing various model formats Postel-Vinay and Turon (2007) consistently found that such models grossly over-predict both job and earnings mobility at lags beyond one or two years. Similarly, restoring the assumption of unobserved earnings classes but reducing the order of the Markov process for earnings to just 1^{st}-order is simpler and quicker to estimate, but again results in substantially larger prediction errors – as compared with the 2^{nd}-order process – at the longer lags. Given that the purpose of our paper is to use the model to construct the lifetime values of individual labour market trajectories, having as good a fit as possible of the earnings mobility is extremely important. Thus the specification using a 2^{nd}-order Markov process, two time-invariant unobserved wage classes and two or three time-invariant unobserved mobility classes, appears to be the right compromise for our purposes.

6.3 *Results – cross-sectional and dynamic differences*

In order to distinguish selection effects from "true" potential differences in all outcomes of interest, we proceed in two stages. In the first one, we simulate *potential* outcomes in both sectors for all individuals in the sample. The "whole sample" figures in our results tables describe these counterfactual outcomes. In a second stage, we simulate outcomes in each sector only for individuals who have selected themselves in that sector in their first period in the sample. The differences obtained, denominated "whole sample, with selection", illustrate differences between sectors for these selected groups of individuals. Table 26 summarises differences in the five dimensions of employment in either sector that we identified above as relevant for the calculation of lifetime values of employment in the public or private sector. These five dimensions are cross-sectional income mean and standard deviation, first auto-covariance of earnings, returns to experience and job loss rate. Results are reported for both sectors in the 5 countries in our sample, as well as for the UK for comparison with our previous results.[23]

The right-hand side panel of Table 26 reports our findings relating to the whole sample with selection. Unsurprisingly, these figures mirror what we observe in the in raw data: the public sector apparently offers a significant positive income premium which is large in Spain (26 log points) and sizable in Italy and France (12 and 13 log points respectively). Public sector earnings exhibit greater persistence, particularly in Italy and Spain. Returns to experience are significantly higher in Germany for employees in the public sector (by 4.7 log points per year), but lower in Italy (by 6.3 log points per year). In the other countries, returns to experience are similar in the selected samples. In accordance with common perception on public sector job security, the job loss risk is significantly lower in the public sector, particularly in Spain. Let us stress once more however that this relates to the selected samples in both sectors. As we will see below, this finding does not always reflect a "true" difference in job loss risk once selection is taken into account.

Comparing the left and the right-hand side panels of the Table allows us to assess the extent of the selection occurring between the two sectors of employment. The most striking difference lies in the income means figures where we observe a substantial positive selection into the public sector, particularly in the Netherlands and Spain. The raw difference in income means between Dutch public and private sector employees is significant and positive at 9 log points, whereas we estimate the counterfactual "true" difference to average over the whole sample as a significant *negative* 4 log points. In Spain, the raw difference is the largest in the countries in our sample, at 26 log points, whereas the counterfactual difference is at a less surprising 11 log points, both significant. So, even when controlling for selection, the Spanish public sector offers a income premium over private sector employment of over 10%, the largest true income premium in our sample. Now turning to the other dimensions of differences, we estimate little selection effect in terms of income persistence or returns to experience. Looking at differences in job security, we see that more

[23]See Postel-Vinay and Turon (2007).

stable employees select in the public sector in Germany as controlling for selection in our counterfactual estimation suggests a higher job loss rate in the public sector by 2.6% (annually), whereas the public sector appears to offer more job security in the selected sample, with a lower apparent job loss rate by 2.6%, both statistically significant. In Spain, differences in job loss risk between the "whole sample" and the "whole sample with selection" panels suggest that 'high unemployment' types select themselves predominantly in the private sector: the significant job loss rate advantage of the public sector becomes smaller and statistically insignificant once selection is controlled for. These results are consistent with the fact that the public sector tends to attract more educated and experienced individuals.

This non-random sorting into employment sectors, whereby a positive selection into the public sector seems to occur, echoes both Hartog and Oosterbeek (1993) and Van Ophem (1993)'s findings for the Netherlands. In our French sample, we find that this positive selection into the public sector explains around three-quarters of the raw public premium.

Now examining the left-hand side panel of the Table, we are able to evaluate the *potential* differences that individuals in our sample would experience (on average) between the two sectors, were they continuously employed in either the private or the public sector. As detailed above, the "true" public premium in mean income, abstracting from selection effects, is still large, significant and positive in Spain at 11 log points. Returns to experience are found to be higher in the public sector in Germany by 5.4 log points per year and lower in the public sector in Italy by 6.3 log points per year. Returns to experience are similarly lower in the public sector in Spain though the difference is not quite statistically significant. Finally, once selection effects are taken into account, the common perception that public sector employment is more secure all other things equal is not confirmed by our analysis in most cases: in Germany, we find a negative public premium in terms of job security as the annual job loss rate in the public sector is 10.2% vs 7.6% in the private sector. In each of the other four countries however, differences in job loss rates are minimal and non-significant once the impact of selection has been removed.

Our results for Germany are in line with the findings of Dustmann and van Soest (1998) who consistently found a significant negative public premium, reducing in age (experience). In France, the true public premium is largest at the bottom of the income distribution (see Table 27, more on which below), which supports Bargain and Melly's (2008) finding that blue collar workers gain the most from public sector employment in France.

6.4 *Summary of Results*

We can now summarize our results along four main points as follows:

- We find evidence of unobserved heterogeneity both in terms of job mobility and in income levels and dynamics. Including it in our model specification is very useful, particularly in allowing us to fit the persistence of labour market states and incomes at longer lags – which is a priority in this paper given that we aim to estimate lifetime value differences.

- Our model specification offers a very good fit of our data in all the dimensions that we examined and gives credibility to the measure of lifetime values that we will be constructing in the next section.

- All five dimensions of public-private differences that we examine matter to forward-looking individuals: dynamics of earnings and employment as well as differences in spot incomes are estimated and found to be different. Once selection has been controlled for, there is a small but significant positive public premium in cross-sectional earnings in France, Italy and the UK (3, 4 and 3 log points respectively). In Spain, this premium is substantial: plus 11 log points. However, in Germany and the Netherlands, public sector earnings offer a small *negative* income premium, of -2 and -4 log points respectively, though this is significant only in the Netherlands. For each country, earnings persistence is greater in the public sector than in the private sector, though only in Italy is the difference statistically significant. Returns to experience are higher in the public sector than in the private sector in Germany (by 5 log-points) and lower in Italy (by 6 log-points). In accordance with a recurring result in the literature, we find more income compression in the public sector. The standard deviation of log-earnings is lower in the public sector for all countries (and for the most part it is a significant difference), the difference being stark in the Netherlands (5 log points lower). Finally, predicted (potential) job loss rates are marginally lower in the public sector.

- Selection into sectors has a large impact. The public sector tends to attract more educated, more experienced and more stable individuals. This selection drives a large fraction of the observed raw differences in income levels and job security.

7 The Public Pay Gap: Earnings and Lifetime Values

In this section we develop a more systematic analysis of the differences between the sectors in terms of lifetime values. We will first define and construct these lifetime values, then carry out counterfactual simulations in which individuals are simulated for a 'lifetime' in each sector. Of course, spending a whole career in one sector or the other may not be the optimal choice for an individual worker. We however find it informative from the point of view of the policy debate to compare the lifetime values of the two "extreme" trajectories of a whole career in a public sector versus a whole career in the private sector. This allows us to contrast our results regarding the public premium with what is usually referred to in the public debate as a measure the relative (dis)advantage of public sector employment, namely the difference in instantaneous earnings between the two sectors. We thereafter comment on the differences in lifetime values obtained under these assumptions with regard to how they relate to the differing institutional and labour market structures within each country.

7.1 Construction of Lifetime Values

The notion of lifetime value that we shall use is the present discounted sum of future income flows, which is the relevant measure when individuals are either risk-neutral or can insure perfectly. Using our estimated coefficients for earnings distributions, and earnings and job mobility, we can carry out simulations of employment and earnings trajectories for the individuals in our sample until retirement age which we assume to happen at a level of experience denoted T_R. In retirement a given individual enjoys a present discounted sum of future earnings stream of V_R (defined below). Given these assumptions, the lifetime value at experience level t of an individual's simulated future earnings trajectory $\mathbf{y}_{s\geq t}$ is written as:

$$V_t\left(\mathbf{y}_{s\geq t}\right) = \left[\sum_{s=t}^{T_R} \beta^{s-t} \cdot \exp\left(y_s\right)\right] + \beta^{T_R - t} \cdot V_R, \tag{12}$$

where $\beta \in (0,1)$ is a discount factor and $\exp\left(y_t\right)$ is the earnings flow that the individual receives at experience level t (y_t designates log earnings). At each level of experience t, current log earnings y_t are conditional on the individual's characteristics and labour market state, as set out in the statistical model of section 5 and more specifically spelled out in Appendix E.

For all countries we set the discount factor to $\beta = 0.95$ *per annum*. The value of retirement, V_R, is defined as $V_R = \frac{1-\beta^{20}}{1-\beta} \times RR \times \exp\left(y_{T_R - 1}\right)$, where RR designates the replacement ratio. Thus we assume that after retirement, individuals receive a constant flow of income equal to RR times their last earnings in employment and discount this flow over a residual life expectancy of twenty years. We calibrate the value of RR to 0.40 and the experience level at retirement to 45 years. While these values will be a more accurate reflection of reality in some countries than others, again in the interest of having a common framework for all countries, we impose these common parameters. As a robustness test we re-estimate with different values of the replacement rate for each country*sector, with values guided by the best estimates in the literature. The impact on lifetime values premia is negligible in almost all cases, since the pension income is heavily discounted for the majority of individuals in each dataset, see Appendix H.[24]

One caveat that must be flagged at this point, is that in conducting this lifetime simulation exercise, we have to assume that, in each country, the economic environment is stationary. We assume that agents anticipate getting older and experiencing wage mobility and job mobility given their current wage and job status, but that they do not anticipate any changes in the model parameters over the remainder of their working lives. For this to be a reasonable assumption it requires our sample time period in each case to be a fairly representative of the average state of the business cycle. As is demonstrated in Appendix D it is a reasonable assumption in each country. Whilst it is unlikely that the economic environment does remain stable throughout their working life, the assumption of stability is the best guess individuals may make when forming expectations of their lifetime earnings stream.

We run a series of counterfactual simulations in which we constrain the probability of moving between sectors or into unemployment to be zero. That is, we assign individuals to a 'job for life' in each sector and simulate their earnings trajectories. This yields the *potential* public premium in lifetime values that we denominate ("whole sample") differences. As for cross-sectional earnings, our second comparison of lifetime values forces individuals to remain in the sector of employment in which they are first observed in our sample over their whole lifetime. This comparison is referred to as "whole sample, with selection". This exercise seems a useful way to simulate careers in a single sector. Indeed, an individual with a strong tendency to work in the private sector, if initially placed in the public sector and allowed to lose his/her job will find subsequent employment in the private sector with a very high probability and pursue his/her subsequent career within that sector. As a consequence, any observed public premium will only be derived from years spent in that sector prior to a first unemployment episode (this is illustrated in the Figures in Appendix H). Of course, this counterfactual exercise is a possible alternative to the one we chose to carry out. Our choice is guided by a desire to measure the maximum extent that this premium could reach, were individuals forced to stay for a whole working life in one sector as opposed to the other.

7.2 Lifetime Values Results

We look at the public premium both in log-earnings and in log-lifetime values at the 10th, 50th and 90th percentile of their distributions. The public premium is defined as the difference between the log earnings

[24]The exception is in Italy where the public premium in lifetime values is increased by approximately two log points across the distribution when a significantly more generous public RR is implemented, which is in line with what we would expect.

(resp. log lifetime value) in the public sector and the private sector. Our results are displayed in Tables 27 and 28.[25] We will now comment on the contrast between differences in lifetime values and differences in terms of earnings and examine the public premia we estimate once controlling for selection. Then we will assess the impact of selection on estimated lifetime value differences. Finally, we will be looking at 'raw' differences in lifetime values, including the impact of non-random selection, and compare inequalities within sectors in the short and long run. In each case, for better ease of reading, we will only be referring in the text to the figures representing the most striking results – figures for every country can be found in Table 27.

The first thing to note is that the public premium in terms of cross-sectional earnings does not necessarily reflect the public premium in terms of lifetime values because of the differences in the dynamic characteristics of employment in either sector. Presumably, forward-looking individuals care about lifetime values more than about spot income only, hence our argument that more emphasis should be put on a fuller picture of public-private differences.

Looking at the "whole sample" panel, i.e. controlling for selection effects, the public premium at the 10th percentile in Italy is an insignificant negative 2 log points, whereas the difference in log-earnings on the same percentile is a positive and significant at 8 log points. For Spain the pattern is similar: the premium in lifetime values at the 10th percentile is 8 log points, the corresponding figure for log-earnings is 18 log points. These patterns are explained by the fact that public sector earnings are more persistent, which adversely affects lifetime values at the bottom of the distribution, and that returns to experience are found to be lower in the public sector in Italy and Spain. In both these countries, these two effects counteract each other at the top of the distribution so that public premia are very similar at the 90th percentile in terms of income or lifetime values. On the other hand, the public premium in terms of income *understates* the public premium in lifetime values by 3 to 5 log points in the middle of lower part of the distribution in France and in the middle and upper parts of the distribution in Germany. Here returns to experience are larger in the public sector and income persistence is not significantly different across sectors, resulting in this greater lifetime values premium *vis-a-vis* log-earnings. Unlike in our previous results obtained for the UK (included in the bottom section of the Table for comparison), we observe some sizable lifetime values public premia in some countries/distribution percentiles: workers enjoy a substantial positive public premium in lifetime values in France and Spain across the distribution, particularly the middle and lower parts, ranging

[25]Note: Tables 27 and 28 include premia in initial period wages to provide a comparison with lifetime values; Table 26 simulates cross sectional wages in three successive periods in order to utilise the second-order Markov model of wage evolution, hence as wages increase with experience the mean figures are slightly higher in Table 26 but premia remain the same.

from +6 (respectively +7) log points at the 50th percentile up to +9 (resp. +8) log points at the bottom of the distribution. By contrast, a substantial *negative* lifetime public premium is found at the top of the distribution in the Netherlands (-5 log points).

Turning now to the right-hand panel of Table 27, i.e. the premia relating to the "whole sample, with selection", and comparing it with "whole sample" results, we find that positive selection prevails in all countries in our sample, across the distribution of lifetime values. The positive selection is most pronounced at the 90th percentile in France and Italy, slightly less so in Germany and the Netherlands, and across the distribution in Spain. Thus both in terms of earnings and lifetime values, selection effects are important: the public sector has a much greater proportion of highly educated workers (for example, 51.0% in the public sector versus 28.7% in the private sector in Spain), and has more experienced workers. This echoes Lassibille's (1998) findings for Spain.

The largest "raw" differences in lifetime value premia are found in Spain and France across the board, though we can see by comparing these premia to their corresponding values in the left-hand panel that a large fraction of these is due to the selection of individuals with higher long-term prospects into the public sector. Other sizable lifetime values public premia in the selected samples are found at the 10th percentile in Germany, the Netherlands and the UK, at around +8 log points, and also at the 50th percentile in Germany, the Netherlands and Italy. These premia at the median go from zero or even negative and non-significant in the selection controlled sample to significant and between 4 and 6 log points in the selected sample. Similarly, for Italy at the top of the distribution the effect of selection is to turn an insignificant premium of 2 log points into a significant 15 log point premium, again reflecting the greater human capital and earning potential of those selecting into the public sector.

With regards to the dispersion of lifetime values, as has been mentioned above, the dispersion of cross-sectional incomes is not very informative of long-run inequality in the presence of income mobility. This is particularly relevant when comparing dispersion between two sectors where the volatility of income is different. Looking at the dispersion of lifetime values gives a more accurate picture of long-term inequality within each sector. Comparing dispersion in cross-sectional income with the dispersion in lifetime values is informative on the relative share of the variance in the permanent income component within the variance of earnings. Postel-Vinay and Turon (2007) found that the greater dispersion of private sector income relative to public sector incomes in the UK was wholly due to a greater dispersion of the transitory component of income. Indeed, when looking at lifetime value estimates, we observed very similar dispersion across the two sectors, suggesting that income inequality was greater in the private sector but longer-lasting in the public sector.

In the five countries we are looking at in this paper, we only find a similar result for Spain (see Table 28). In Spain, the standard deviation of incomes is 0.35 in the private sector versus 0.30 in the public sector, whereas the standard deviation of lifetime values is the same for both sectors. This suggests that, in Spain, the greater pay compression in public sector earnings is driven by a lower variance of the transitory component of earnings in the public sector, as we had found in the UK. The results for France and Italy do not exhibit the same feature hinting at no such dissimilarity between the relative shares of variances in the transitory and permanent income components in these countries. For Germany and the Netherlands, both log earnings and lifetime values have significantly less dispersion in the public than the private sector, to approximately the same extent. This suggests that both the permanent and transitory components of income are less dispersed in the public sector for these countries and both contribute to the greater equality of pay in that sector.

8 Institutional Differences and Public Premia

While our model does not seek to explain the differences in public pay and lifetime values that we find across countries, it is instructive to consider how the differences that we do find relate to the institutional context within each country. As noted in section 3, for the most part the institutions and structures that determine public and private sector pay are very similar across the group of countries in our study. The most notable exception to this is the Netherlands: along a number of dimensions, the Netherlands is something of an outlier. It may be for reasons related to this that we find – after controlling for selection – a significant negative public premium in wages at the mean and at the top of the wage distribution, and also at the top of the distribution of lifetime values. The Netherlands is the only country that does not have a clearly defined career path and largely deterministic pay scale for their civil service, moreover the office of civil servant is not invested with the same level of privilege and security as is the case in the other countries. This greater flexibility in pay setting in the public sector – and lack of protection of pay for civil servants – may make an important contribution to the public sector penalty in wages at the mean. In addition, there is less pay dispersion in the public sector in the Netherlands which may be because of this difference in entry requirements for the civil service. As the costs to attain the highest tier jobs are lower, thus reducing the need for compensating differentials at the top, the public pay distribution is compressed. Similarly, in

Germany where there are no entry exams to access the civil service the premium at the top is negative, though not statistically significant.

Seniority plays a large part in remuneration in Germany and we see this reflected in the significantly higher returns to experience in the public sector. This may be capturing the additional pay related to marital and family status for civil servants in Germany which is more likely to impact the upper half of the age distribution.

France, Spain and Italy are the countries that are most similar to each other in terms of their labour market institutions and structures. This may explain why they are the only countries which, after controlling for selection, retain a positive public premium at the mean in wages and, for the former two at least, in lifetime values too. Indeed, in France, Italy and Spain there are positive premia in wages and lifetime values at the 90th percentile of their distributions – though these are not statistically significant – in addition to significant premia at the bottom and the middle of the distribution. These countries are similar with respect to the recruitment and pay of their civil servants and it is perhaps the cost of entering the civil service in particular that is reflected in a lifetime values premium in the middle and top in the public sector in these countries, capturing something of a compensating differential. These countries are also the most similar in terms of their collective bargaining arrangements and union power in general in the public sector. This leads to a more egalitarian pay structure – to the benefit of the lower to medium skilled workers who gain a greater relative premium. Spain is notably the country with the greatest difference between the premia at the top and the bottom of the distribution both in earnings and lifetime values. Though there is a premium at the top, the premia lower down the distribution are much greater and are significant. This is particularly striking for log earnings where the 10th percentile premium is approximately four times the size of that at the 90th percentile in Spain, with only a slightly smaller ratio in Italy and slightly smaller still in France. This may be partly explained by the high proportion of fixed-term contracts in Spain, particularly in the private sector. These contracts are associated with lower pay than permanent employment contracts and this is likely to add to the premium in earnings in particular in the lower part of the distribution in Spain (see Amuedo-Dorantes and Serrano-Padial, 2005).

However, compared with the private sector, the rigid pay structures in the Spanish and Italian public sectors leads to them having lower returns to experience, significantly so in Italy. As noted above, this reduces the lifetime value premium relative to the wage premium at the bottom of the distribution in Italy and Spain.

The remaining significant finding that may be related to differences in institutional structures concerns the higher job loss rate in the public sector for Germany. The fact that almost half of the German public sector workers (45%) are on private law labour contracts (the so called “Angestellte”) that do not offer the employment protection of the civil service may explain why we do not find the same benefit in terms of lower job loss rate in Germany that we do in most of the other countries.

9 Conclusions

Regardless of the country, the literature on public-private pay differences tends to focus on cross-sectional differences in earnings, and the extent to which they can be ‘explained away’ by selection. However, as the sectors also differ in terms of earnings mobility and job mobility, these factors need to be taken into account in any assessment of the long-term public-pay gap. In a dynamic environment forward-looking agents care about their job security and earnings dynamics and anticipate that these differ between the sectors and this will affect their assessment of the lifetime value of potential employment in either sector. To derive a more informative comparison of pay in the public and private sectors, we apply a flexible model of earnings and employment dynamics, where the individual earnings and employment trajectories are conditioned by unobserved as well as observed individual heterogeneity.

We estimate the model on ECHP data for Germany, the Netherlands, France, Italy and Spain (plus the UK to provide a comparison). This is the first time that a dynamic approach to public-private pay differentials has been applied to these European countries, using the same model and dataset. In each of the countries we are able to fit well the observed cross-sectional distribution of workers into sectors and the cross-sectional earnings distributions. Importantly for our purposes, we also fit the patterns of labour market mobility and earnings mobility very well. A recurring result is that selection is an important contributor to all differences observed in the raw data. After controlling for selection, we find substantial differences in potential outcomes in all five dimensions of employment we are interested in: spot incomes are larger in the public sector in France, Italy, Spain and the UK, but lower in the Netherlands. There is a positive public premium in terms of returns to experience in Germany, but this premium in negative in Italy. Public sector earnings exhibit greater persistence in all countries, particularly so in Italy. As in the raw data, we estimate greater income compression in the public sector in all countries in our sample. Finally, and contrary to perceptions in the public debate, there are no large discrepancies between job loss risks in both sectors. In fact, in Germany, the job loss risk in the public sector is higher than in the private sector.

When we aggregate these differences into our measure of lifetime value of employment in either sector, we find sizable potential premia for some workers: individuals across the income distribution in France and Spain face a positive lifetime premium, particularly in the middle to lower ranges: decreasing from 8-9 log-points for individuals at the bottom of the distribution to 6-7 log-points in the middle before reducing to 3-5 log points (and not statistically significant) at the top. A negative public premium in lifetime values is found at the top of the distribution in the Netherlands: 5 log-points in favour of the private sector. While income inequality in Spain results from the transitory component of earnings contributing a higher share of the total variance, in Germany and the Netherlands the level of inequality in the distribution is a result of both the permanent and transitory components.

Our findings confirm that any assessment of the "public premium" needs to take account not only of non-random selection of workers into sector but also of the dynamic differences between the sectors. These dimensions of difference compound over a lifetime and result in a lifetime values public premium that can be very different to the picture implied by looking simply at spot income differences.

We compare our findings with public sector and labour market institutions in the countries in our dataset to highlight possible links between institutions and lifetime public premium. Our common dataset, time-period and modelling approach allows us to rule out the differences in lifetime premia resulting from differences in the source of data or empirical model. While the majority of countries in our data are similar in respect of the institutions and structures that determine recruitment and pay in the public and private sectors, the one outlier – the Netherlands – is the only country to have a significant negative public premia in lifetime values at the top of the distribution. The countries that are most similar and in particular the ones that have the most stringent barriers to overcome in order to enter the civil service – France, Italy and Spain – have significant premia at the mean, median and across the distribution of earnings, and for France and Spain in lifetime values also. Examining a potential causality mechanism between institutions and public sector lifetime premium with a theoretical model thus seems an interesting avenue for future research and policy choices.

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10 Descriptive Tables

		N	%	$\overline{T}$
Germany	Total	3402	100.0%	6.9
	Private	2422	71.2%	6.9
First observation	Public	614	18.0%	7.1
	Unemployed	366	10.8%	6.4
Netherlands	Total	2564	100.0%	6.7
	Private	1858	72.5%	6.7
First observation	Public	566	22.0%	6.8
	Unemployed	140	5.5%	6.1
France	Total	2619	100.0%	6.2
	Private	1634	62.4%	6.3
First observation	Public	660	25.2%	6.4
	Unemployed	325	12.4%	5.8
Italy	Total	4567	100.0%	6.6
	Private	2664	58.3%	6.7
First observation	Public	882	19.3%	6.7
	Unemployed	1021	22.4%	6.2
Spain	Total	3689	100.0%	6.6
	Private	2311	62.6%	6.7
First observation	Public	527	14.3%	6.7
	Unemployed	851	23.1%	6.2

Table 1: Sample Statistics

		Germany	Netherlands	France	Italy	Spain
Private Sector	Median	41	40	39	40	40
	St. Dev.	7.41	6.94	7.10	5.22	7.73
Public Sector	Median	40	38	39	36	40
	St. Dev.	6.22	5.28	5.66	4.27	6.39

Table 2: Weekly Hours distribution by sector

		Education				
		High	Medium	Low	Age (years)	Experience* (years)
Germany	Overall	29.3	60.2	10.5	39.1	20.0
	Private	28.8	60.2	11.1	38.7	19.8
	Public	37.9	58.8	0.3	40.7	20.8
	Unemp	19.3	68.2	18.0	38.5	20.1
Netherlands	Overall	25.2	56.3	18.4	40.4	21.2
	Private	20.5	59.9	19.6	39.8	20.6
	Public	44.0	45.7	10.3	43.1	23.2
	Unemp	16.9	47.9	35.1	39.3	20.4
France	Overall	27.1	44.8	28.1	39.2	20.3
	Private	23.9	47.2	28.9	39.0	20.3
	Public	35.8	41.7	22.5	40.9	21.7
	Unemp	24.3	37.0	38.7	35.6	16.7
Italy	Overall	10.5	49.5	40.0	37.9	19.9
	Private	7.6	47.4	45.0	38.7	21.0
	Public	19.6	54.8	25.6	42.2	23.0
	Unemp	10.5	50.9	38.6	29.9	11.7
Spain	Overall	33.0	23.7	43.3	38.1	20.8
	Private	27.8	24.1	48.1	38.7	21.7
	Public	58.9	21.4	19.7	40.5	21.8
	Unemp	31.6	24.0	44.4	33.7	16.3

* Experience is *potential* labour market experience i.e. current age minus the age when the individual first entered the labour market.

Table 3: Human Capital

		Germany		Netherlands		France		Italy		Spain		UK	
		Private	Public	Private	Public	Private	Public	Private	Public	Private	Public	Private	Public
wage…	…mean	8.44	8.48	8.69	8.78	9.38	9.51	7.91	8.01	12.22	12.49	7.43	7.53
	…std. dev.	0.37	0.33	0.33	0.30	0.43	0.39	0.30	0.29	0.43	0.40	0.42	0.38
	…1-period auto-covariance	0.80	0.90	0.87	0.88	0.81	0.91	0.71	0.89	0.74	0.88	0.81	0.87
	1-period job loss rate	5.6	3.2	1.9	1.5	4.0	2.1	3.5	1.6	6.4	3.5	3.5	2.2

Table 4: Raw earnings and job loss differences by sector

11 Results Tables

11.1 *Unobserved Heterogeneity*

Unobserved heterogeneity class	1	2	3	4	5	6	Total
	$k^m = 1$	$k^m = 2$	$k^m = 3$	$k^m = 1$	$k^m = 2$	$k^m = 3$	
	$k^y = 1$	$k^y = 1$	$k^y = 1$	$k^y = 2$	$k^y = 2$	$k^y = 2$	
Germany	0.83	31.38	12.97	17.47	29.48	7.87	100.00
Netherlands	13.18	30.34		16.16	40.32		100.00
France	21.43	17.87		50.85	9.85		100.00
Italy	7.14	24.23	15.72	3.48	36.45	12.98	100.00
Spain	10.23	25.65	17.43	5.51	34.58	6.60	100.00

Table 5: Distribution of individuals across mobility and wage classes

Mobility classes	% high ed.	% med. ed.	% low ed.	Mean. . . . . . exp.	. . . (log) wage	. . . public sector	. . . unemp.
$k^m = 1$	18.46	64.88	16.65	16.14	8.25	0.089	0.362
$k^m = 2$	29.03	59.07	11.90	16.83	8.43	0.000	0.055
$k^m = 3$	37.09	59.96	2.95	16.14	8.47	0.788	0.037
Wage classes							
$k^y = 1$	26.89	66.59	6.52	16.05	8.49	0.231	0.045
$k^y = 2$	30.33	55.15	14.52	16.97	8.35	0.139	0.160
Total	28.78	60.32	10.91	16.56	8.42	0.180	0.108

Table 6: **Germany**: Composition of Unobserved Heterogeneity Classes

Mobility classes	% high ed.	% med. ed.	% low ed.	Mean......exp.	...(log) wage	...public sector	...unemp.
$k^m = 1$	40.51	45.05	14.44	18.54	8.76	0.753	0.127
$k^m = 2$	18.67	58.07	23.26	17.50	8.65	0.000	0.025
Wage classes							
$k^y = 1$	33.97	37.23	28.79	17.50	8.69	0.231	0.057
$k^y = 2$	18.22	67.37	14.41	18.04	8.67	0.213	0.053
Total	25.08	54.25	20.67	17.80	8.68	0.221	0.055

Table 7: **Netherlands**: Composition of Unobserved Heterogeneity Classes

Mobility classes	% high ed.	% med. ed.	% low ed.	Mean......exp.	...(log) wage	...public sector	...unemp.
$k^m = 1$	26.41	47.16	26.43	20.10	9.41	0.310	0.010
$k^m = 2$	28.81	36.81	34.38	9.45	9.21	0.101	0.421
Wage classes							
$k^y = 1$	38.09	37.58	24.33	16.25	9.49	0.235	0.202
$k^y = 2$	19.94	48.64	31.43	17.73	9.31	0.263	0.073
Total	27.07	44.29	28.64	17.15	9.37	0.252	0.124

Table 8: **France**: Composition of Unobserved Heterogeneity Classes

Mobility classes	% high ed.	% med. ed.	% low ed.	Mean......exp.	...(log) wage	...public sector	...unemp.
$k^m = 1$	8.70	48.70	42.60	14.75	7.86	0.082	0.708
$k^m = 2$	13.34	48.40	38.26	17.40	7.92	0.269	0.084
$k^m = 3$	5.50	52.29	42.21	15.44	7.89	0.073	0.340
Wage classes							
$k^y = 1$	15.05	48.52	36.43	19.29	7.98	0.207	0.223
$k^y = 2$	6.63	50.47	42.90	14.12	7.86	0.180	0.224
Total	10.60	49.55	39.85	16.56	7.91	0.193	0.224

Table 9: **Italy**: Composition of Unobserved Heterogeneity Classes

Mobility classes	% high ed.	% med. ed.	% low ed.	Mean……exp.	…(log) wage	…public sector	…unemp.
$k^m = 1$	60.28	23.35	16.36	17.06	12.47	0.875	0.073
$k^m = 2$	27.50	24.82	47.68	17.17	12.16	0.000	0.116
$k^m = 3$	28.87	22.67	48.46	16.94	12.13	0.022	0.622
Wage classes							
$k^y = 1$	54.82	23.48	21.70	15.72	12.35	0.173	0.283
$k^y = 2$	8.06	24.74	67.19	18.68	12.11	0.107	0.171
Total	32.99	24.07	42.94	17.10	12.23	0.143	0.231

Table 10: **Spain**: Composition of Unobserved Heterogeneity Classes

11.2 *Mobility Fit*

	Observed				Predicted			
	% of sample	% $k^m = 1$	% $k^m = 2$	% $k^m = 3$	% of sample	% $k^m = 1$	% $k^m = 2$	% $k^m = 3$
Private	71.19	14.12	80.77	5.11	71.66	14.27	80.56	5.17
Public	18.05	9.01	0.00	90.99	18.11	9.00	0.00	91.00
Unemp.	10.76	61.57	31.21	7.21	10.23	63.02	30.64	6.34
	100.00				100.00			

Table 11: **Germany**: Class composition of the sectors, Real and Simulated

	Observed			Predicted		
	% of sample	% $k^m = 1$	% $k^m = 2$	% of sample	% $k^m = 1$	% $k^m = 2$
Private	72.46	4.89	95.11	72.57	5.23	94.77
Public	22.07	100.00	0.00	21.57	100.00	0.00
Unemp.	5.46	68.02	31.89	5.86	67.70	32.30
	100.00			100.00		

Table 12: **Netherlands**: Class composition of the sectors, Real and Simulated

	Observed			Predicted		
	% of sample	% $k^m = 1$	% $k^m = 2$	% of sample	% $k^m = 1$	% $k^m = 2$
Private	62.39	78.76	21.24	63.90	78.87	21.13
Public	25.20	88.86	11.14	23.96	88.45	11.55
Unemp.	12.41	5.99	94.01	12.14	5.63	94.37
	100.00			100.00		

Table 13: **France**: Class composition of the sectors, Real and Simulated

	Observed				Predicted			
	% of sample	% $k^m = 1$	% $k^m = 2$	% $k^m = 3$	% of sample	% $k^m = 1$	% $k^m = 2$	% $k^m = 3$
Private	58.33	3.81	67.30	28.88	58.01	3.31	67.80	28.89
Public	19.31	4.53	84.63	10.84	19.33	4.96	83.72	11.32
Unemp.	22.36	33.63	22.71	43.65	22.66	34.15	22.83	43.03
	100.00				100.00			

Table 14: **Italy**: Class composition of the sectors, Real and Simulated

	Observed				Predicted			
	% of sample	% $k^m = 1$	% $k^m = 2$	% $k^m = 3$	% of sample	% $k^m = 1$	% $k^m = 2$	% $k^m = 3$
Private	62.65	1.31	85.02	13.67	62.14	1.33	85.15	13.53
Public	14.29	96.37	0.00	3.63	14.23	96.69	0.00	3.31
Unemp.	23.07	4.97	30.25	64.78	23.63	4.86	31.02	64.12
	100.00				100.00			

Table 15: **Spain**: Class composition of the sectors, Real and Simulated

	Observed			Predicted			
state at $t-1$	state at t			state at t			
$\downarrow$	private	public	unemp.	private	public	unemp.	
Private	93.1	1.2	5.6	94.4	1.2	4.3	Max distance: 7.6
Public	7.0	89.6	3.2	7.4	89.8	2.6	Max distance, 2x2: 1.3
Unemp.	32.7	5.1	62.1	38.7	6.6	54.5	
state at $t-5$							
$\downarrow$							
Private	88.2	2.7	9.0	90.7	3.4	5.8	Max distance: 12.9
Public	21.7	73.9	4.3	24.0	73.7	3.1	Max distance, 2x2: 2.5
Unemp.	53.4	8.3	38.1	64.9	9.7	25.5	

Table 16: **Germany**: Fit to Job Mobility Data

	Observed			Predicted			
state at $t-1$	state at t			state at t			
$\downarrow$	private	public	unemp.	private	public	unemp.	
Private	95.9	2.0	1.9	96.3	2.1	1.4	Max distance: 5.5
Public	8.5	89.8	1.5	7.7	91.4	0.8	Max distance, 2x2: 1.6
Unemp.	28.2	4.5	67.2	32.1	6.1	61.7	
state at $t-5$							
$\downarrow$							
Private	93.3	3.3	3.2	93.8	4.0	2.1	Max distance: 25.2
Public	20.2	77.2	2.5	16.9	80.2	2.8	Max distance, 2x2: 3.3
Unemp.	53.0	7.2	39.6	49.1	32.4	18.4	

Table 17: **Netherlands**: Fit to Job Mobility Data

	Observed			Predicted			
state at $t-1$	state at t			state at t			
$\downarrow$	private	public	unemp.	private	public	unemp.	
Private	95.5	0.4	4.0	96.7	0.3	2.8	Max distance: 3.1
Public	0.9	96.8	2.1	0.9	97.6	1.3	Max distance, 2x2: 1.2
Unemp.	29.8	7.4	62.6	32.1	8.2	59.5	
state at $t-5$							
$\downarrow$							
Private	91.3	2.1	6.5	93.2	3.0	3.7	Max distance: 19.5
Public	4.9	92.7	2.3	6.8	91.1	1.9	Max distance, 2x2: 1.9
Unemp.	45.9	9.9	44.0	59.3	16.1	24.5	

Table 18: **France**: Fit to Job Mobility Data

state at $t-1$	Observed			Predicted			
	state at t			state at t			
$\downarrow$	private	public	unemp.	private	public	unemp.	
Private	94.9	1.5	3.5	96.1	1.6	2.2	Max distance: 4.3
Public	5.3	93.0	1.6	5.1	93.8	1.0	Max distance, 2x2: 1.2
Unemp.	18.4	3.3	78.2	21.3	4.7	73.9	
state at $t-5$							
$\downarrow$							
Private	90.1	5.0	4.7	90.9	7.2	1.8	Max distance: 13.0
Public	15.2	82.8	1.8	22.1	77.5	0.3	Max distance, 2x2: 6.9
Unemp.	42.7	9.2	48.0	52.9	12.0	35.0	

Table 19: **Italy**: Fit to Job Mobility Data

state at $t-1$	Observed			Predicted			
	state at t			state at t			
$\downarrow$	private	public	unemp.	private	public	unemp.	
Private	92.0	1.4	6.4	93.4	1.7	4.8	Max distance: 5.6
Public	8.3	88.1	3.5	9.2	88.1	2.5	Max distance, 2x2: 1.4
Unemp.	32.6	3.6	63.7	37.0	4.8	58.1	
state at $t-5$							
$\downarrow$							
Private	90.1	2.5	7.2	92.9	3.1	3.8	Max distance: 7.0
Public	19.1	77.1	3.7	17.7	80.7	1.4	Max distance, 2x2: 3.6
Unemp.	59.7	7.2	33.0	65.7	8.2	26.0	

Table 20: **Spain**: Fit to Job Mobility Data

11.3 *Income Fit*

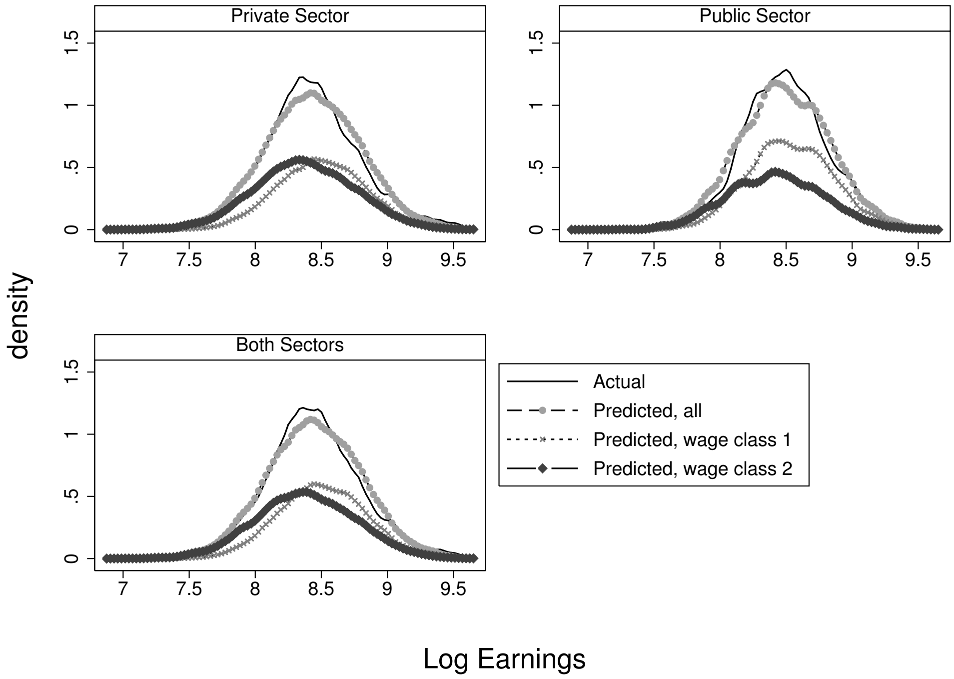

Figure 1: **Germany**: Cross-sectional wage fit

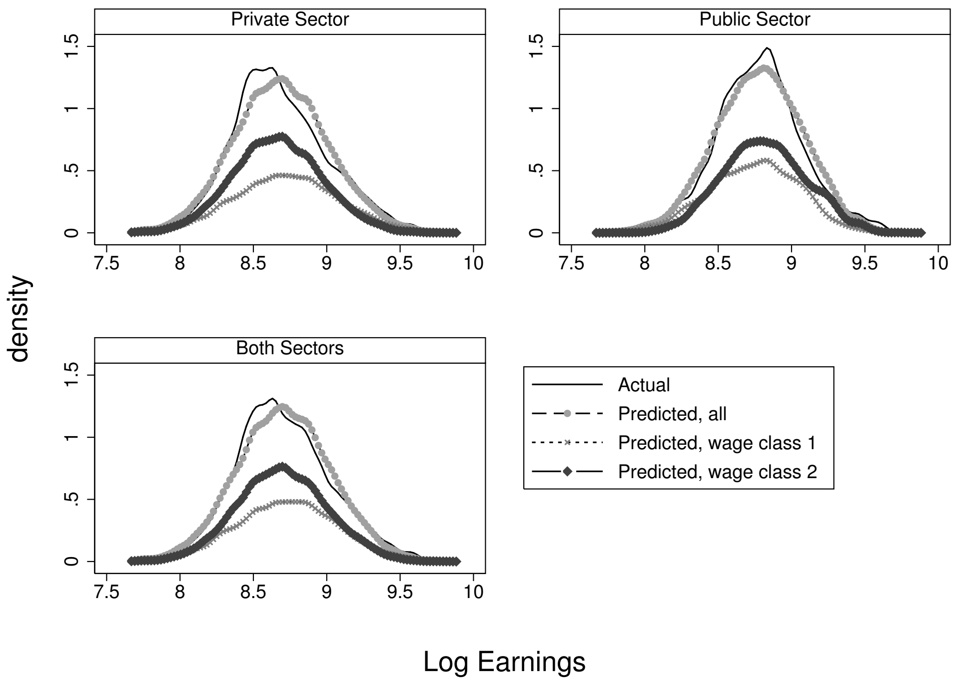

Figure 2: **Netherlands**: Cross-sectional wage fit

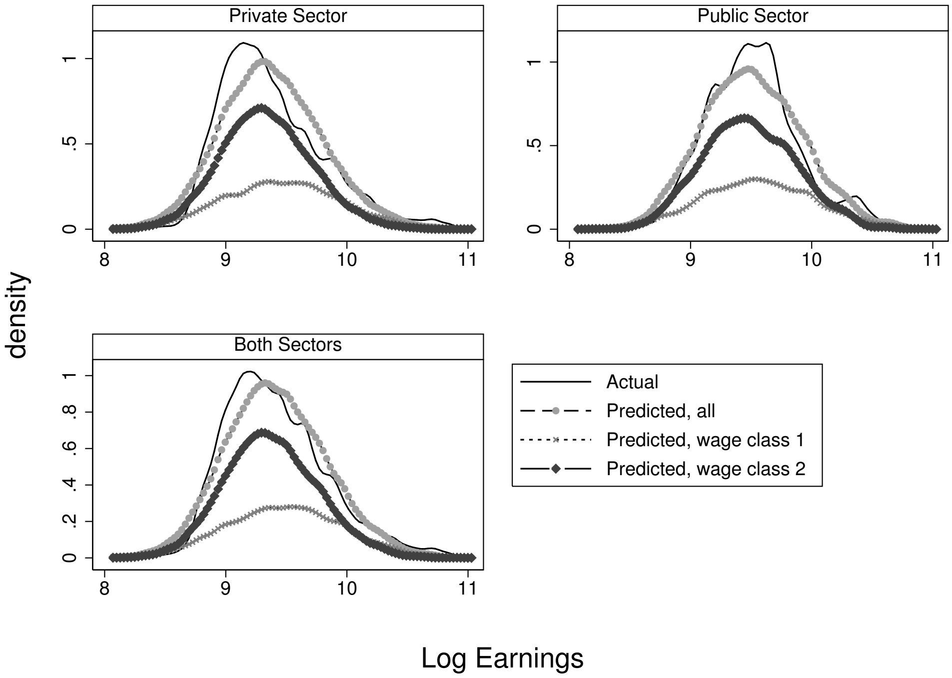

Figure 3: **France**: Cross-sectional wage fit

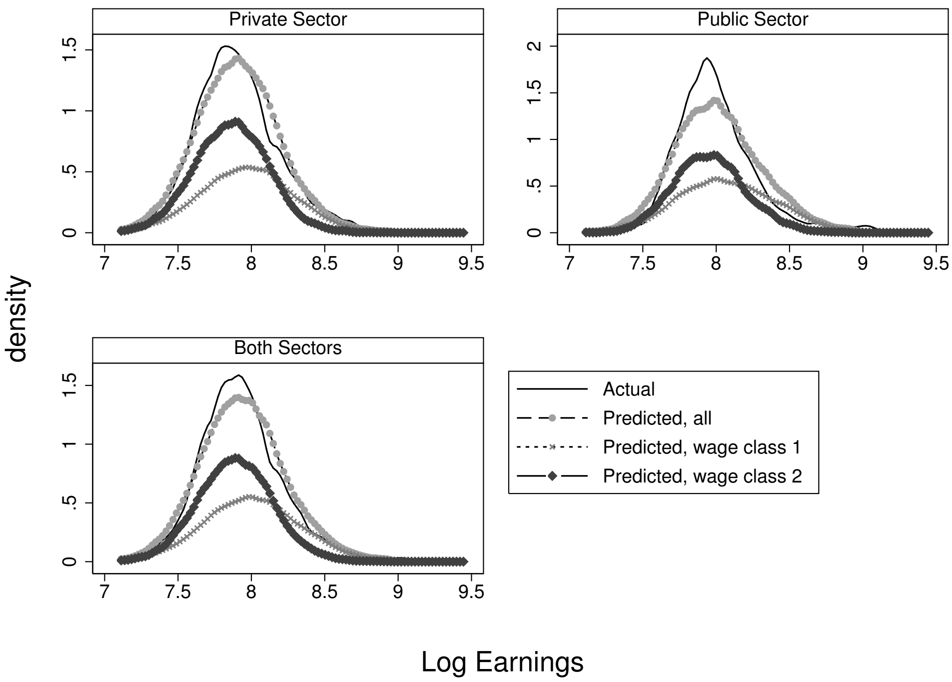

Figure 4: **Italy**: Cross-sectional wage fit

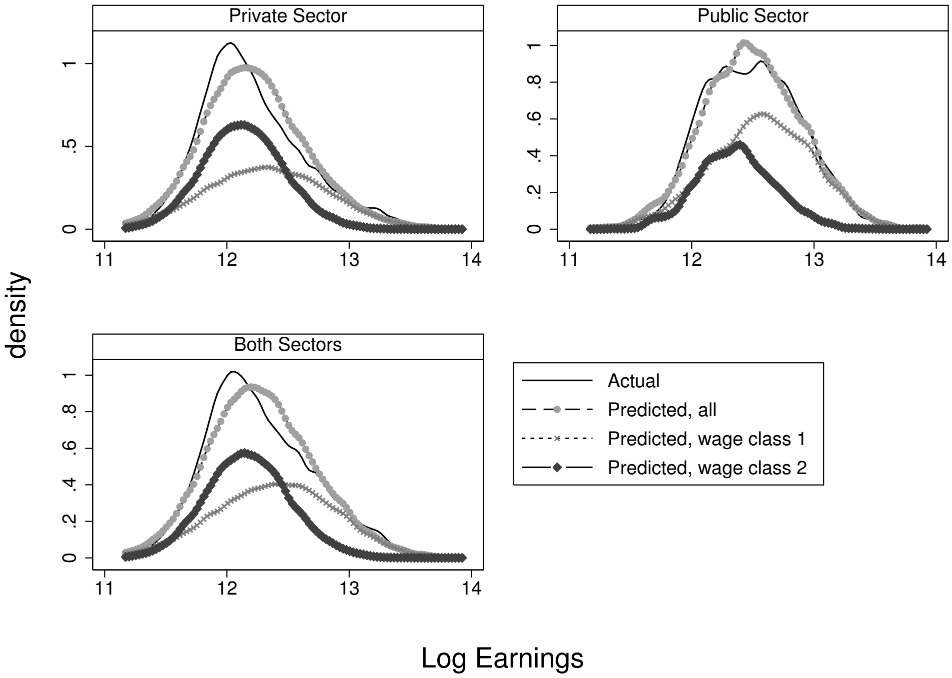

Figure 5: **Spain**: Cross-sectional wage fit

	Observed					Predicted					
	earnings quintile at t					earnings quintile at t					
	75.1	18.9	3.9	1.6	0.3	71.2	21.8	5.1	1.5	0.1	
earnings	17.7	57.2	20.0	4.2	0.6	18.9	49.5	23.7	6.6	1.1	Max. dist.:
quintile	3.4	20.3	54.9	18.8	2.4	3.6	22.2	48.3	21.9	3.9	
at $t-1$	0.8	3.4	19.9	61.0	14.6	0.6	5.1	21.1	55.8	17.0	7.7
	0.1	0.8	2.2	12.6	84.1	0.1	1.0	3.0	16.2	79.5	
	63.9	21.1	7.9	4.2	2.7	53.7	24.2	11.1	7.3	3.5	
earnings	26.3	41.4	21.6	8.2	2.2	23.8	35.9	23.7	12.4	3.9	Max. dist.:
quintile	7.0	28.1	40.0	21.0	3.7	10.2	22.3	35.4	24.3	7.5	
at $t-5$	2.9	9.0	27.2	44.2	16.5	7.2	12.9	22.7	36.6	20.4	13.9
	0.5	1.6	3.0	17.1	77.5	2.9	5.3	7.3	20.7	63.6	

Note: earnings quintiles from the unconditional sample distribution.

Table 21: **Germany**: Fit to Wage Mobility Data

	Observed: earnings quintile at t					Predicted: earnings quintile at t					
earnings quintile at $t-1$	80.1	16.5	2.3	0.7	0.1	81.1	16.3	2.2	0.2	0.0	Max. dist.:
	15.1	66.2	15.6	2.5	0.3	15.1	62.3	19.5	2.7	0.1	
	1.7	16.3	64.7	15.6	1.3	1.5	18.6	58.4	19.7	1.5	
	0.5	1.9	16.7	69.8	11.0	0.3	2.3	18.3	63.2	15.6	6.6
	0.1	0.2	0.8	11.4	87.3	0.0	0.1	1.7	14.6	83.4	
earnings quintile at $t-5$	63.3	23.8	8.6	1.6	2.4	68.3	22.5	6.6	1.6	0.8	Max. dist.:
	25.0	45.0	21.4	7.5	1.0	20.4	45.1	24.6	7.8	1.7	
	3.9	31.5	44.8	14.9	4.6	5.8	22.7	39.9	24.9	6.4	
	1.9	5.1	24.9	53.0	14.8	1.9	7.1	25.2	43.7	21.8	10.0
	0.0	0.6	2.3	22.4	74.4	0.6	2.4	3.5	22.0	71.2	

Note: earnings quintiles from the unconditional sample distribution.

Table 22: **Netherlands**: Fit to Wage Mobility Data

	Observed: earnings quintile at t					Predicted: earnings quintile at t					
earnings quintile at $t-1$	74.6	21.2	3.4	0.4	0.1	76.6	19.1	3.4	0.7	0.0	Max. dist.:
	17.8	59.0	20.6	2.2	0.2	16.4	58.0	21.3	3.9	0.2	
	2.7	16.2	61.6	17.6	1.8	2.0	19.8	55.9	20.0	2.0	
	1.1	2.4	16.4	65.3	14.6	0.3	2.6	18.3	61.9	16.6	5.7
	0.3	0.7	1.7	12.9	84.1	0.0	0.1	1.8	14.7	83.2	
earnings quintile at $t-5$	64.3	25.7	7.2	2.5	0.0	62.4	25.2	7.5	3.4	1.2	Max. dist.:
	18.8	49.3	27.4	3.4	0.8	21.9	42.3	25.8	7.5	2.2	
	3.9	18.9	46.2	24.5	6.3	5.4	23.8	41.6	23.9	5.1	
	1.7	7.0	15.7	55.7	19.7	2.8	5.7	20.7	49.2	21.4	7.0
	1.2	1.6	3.7	15.6	77.6	0.7	1.4	4.6	18.7	74.3	

Note: earnings quintiles from the unconditional sample distribution.

Table 23: **France**: Fit to Wage Mobility Data

	Observed					Predicted					
	earnings quintile at t					earnings quintile at t					
earnings quintile at $t-1$	61.8	24.4	8.7	4.1	0.8	65.7	24.7	7.1	1.9	0.3	Max. dist.: 4.5
	21.5	46.6	21.7	8.2	1.8	21.2	44.0	25.5	7.3	1.7	
	7.4	22.7	45.3	19.5	4.8	5.6	23.6	40.8	23.8	5.9	
	1.8	6.8	23.0	51.2	16.9	1.4	6.0	22.8	48.1	21.4	
	0.7	1.4	4.3	18.8	74.5	0.2	1.4	4.7	20.5	72.9	
earnings quintile at $t-5$	42.3	29.9	15.3	8.1	4.2	46.6	27.2	14.5	8.3	3.1	Max. dist.: 7.9
	22.0	36.5	21.6	15.6	4.0	22.6	31.5	23.8	14.5	7.4	
	10.1	29.5	30.1	21.2	8.8	11.3	21.6	30.7	23.7	12.4	
	5.8	11.2	20.0	40.7	22.1	5.7	12.9	21.9	34.5	24.8	
	1.6	4.6	6.6	24.7	62.3	2.6	6.2	10.4	23.2	57.4	

Note: earnings quintiles from the unconditional sample distribution.

Table 24: **Italy**: Fit to Wage Mobility Data

	Observed					Predicted					
	earnings quintile at t					earnings quintile at t					
earnings quintile at $t-1$	57.7	29.0	10.7	2.1	0.1	64.3	26.5	6.9	1.9	0.2	Max. dist.: 10.9
	22.8	42.6	28.9	5.0	0.5	21.1	44.4	25.4	7.8	1.0	
	6.8	23.4	44.7	22.6	2.3	4.8	22.3	42.1	25.6	5.0	
	0.8	3.9	17.3	59.5	18.2	1.0	5.7	23.6	48.6	20.9	
	0.1	0.3	1.8	16.0	81.6	0.1	0.7	3.5	19.1	76.4	
earnings quintile at $t-5$	43.1	34.8	13.7	6.8	1.3	47.0	25.4	17.6	6.1	3.8	Max. dist.: 18.1
	21.0	39.2	28.2	10.1	1.2	24.2	32.1	22.5	15.2	5.8	
	8.7	20.5	37.6	26.2	6.8	11.6	26.0	28.9	23.9	9.4	
	1.7	9.1	16.4	48.0	24.5	6.1	11.1	25.6	33.2	23.8	
	0.0	1.0	2.1	17.2	79.4	1.8	2.7	9.3	24.7	61.3	

Note: earnings quintiles from the unconditional sample distribution.

Table 25: **Spain**: Fit to Wage Mobility Data

11.4 *Wage Distributions and Returns to Experience*

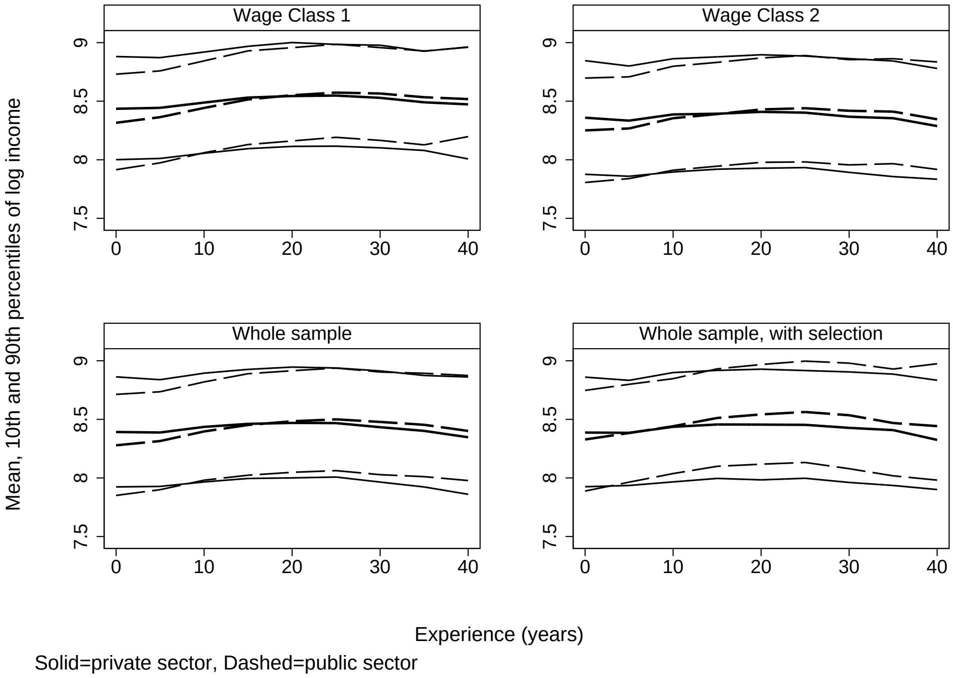

Figure 6: **Germany**: Earnings-Experience Profiles, all and by earnings class

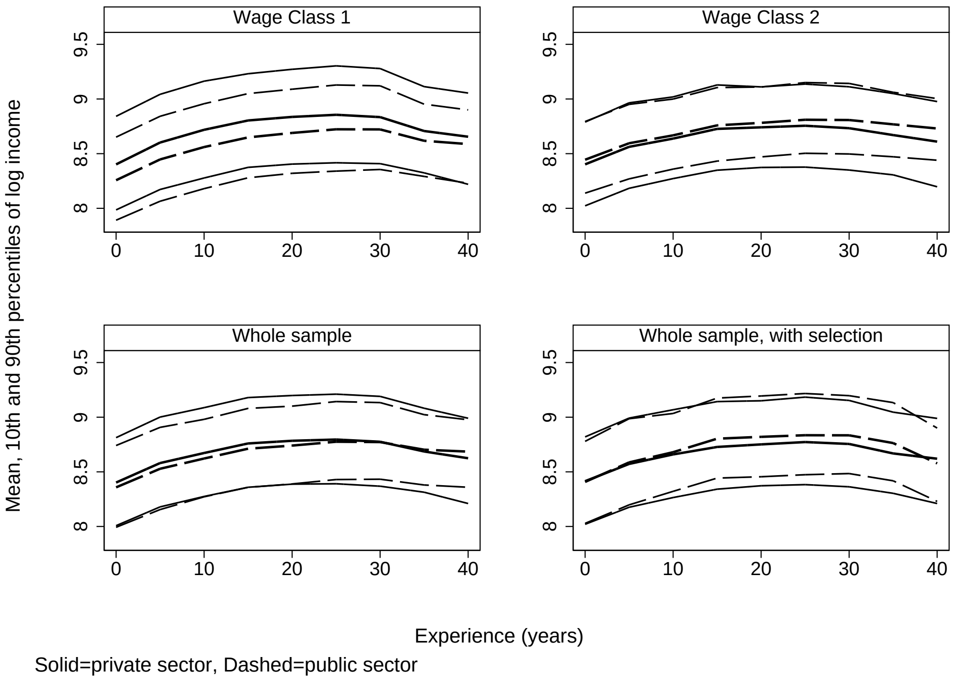

Figure 7: **Netherlands**: Earnings-Experience Profiles, all and by earnings class

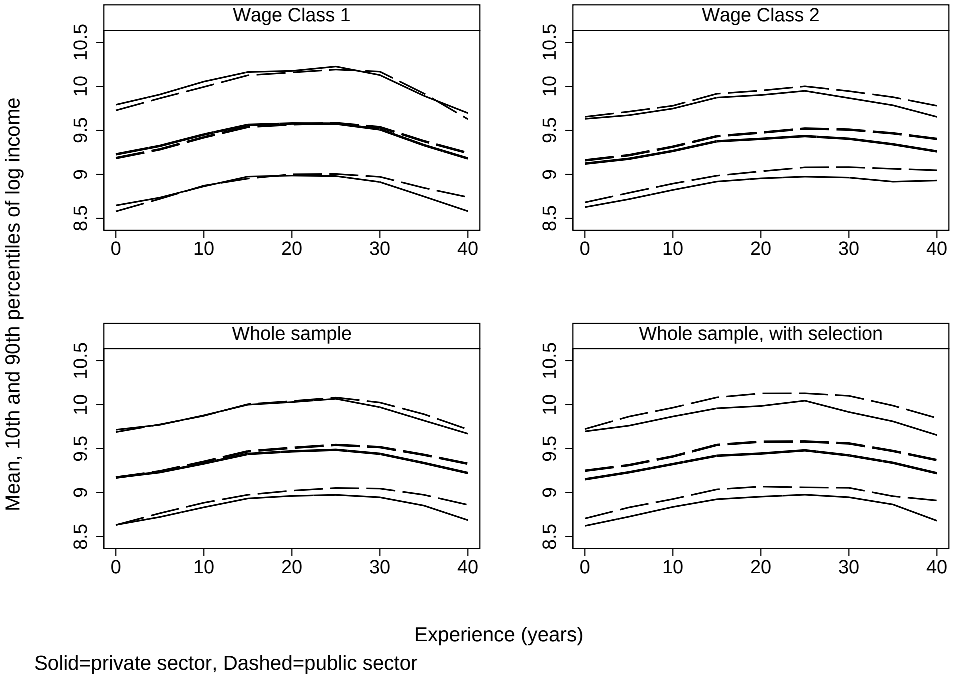

Figure 8: **France**: Earnings-Experience Profiles, all and by earnings class

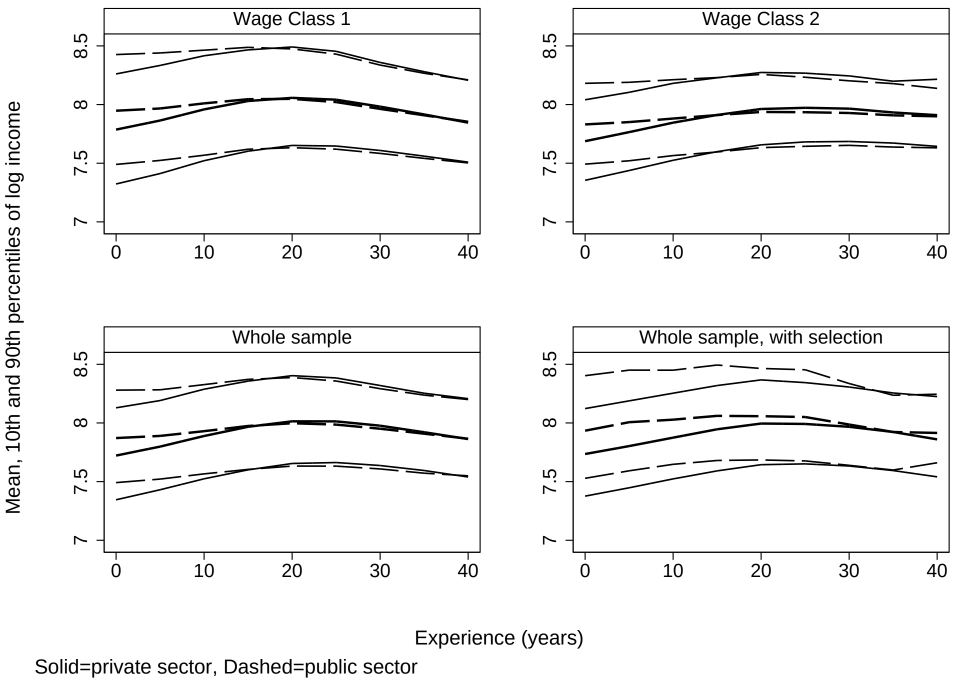

Figure 9: **Italy**: Earnings-Experience Profiles, all and by earnings class

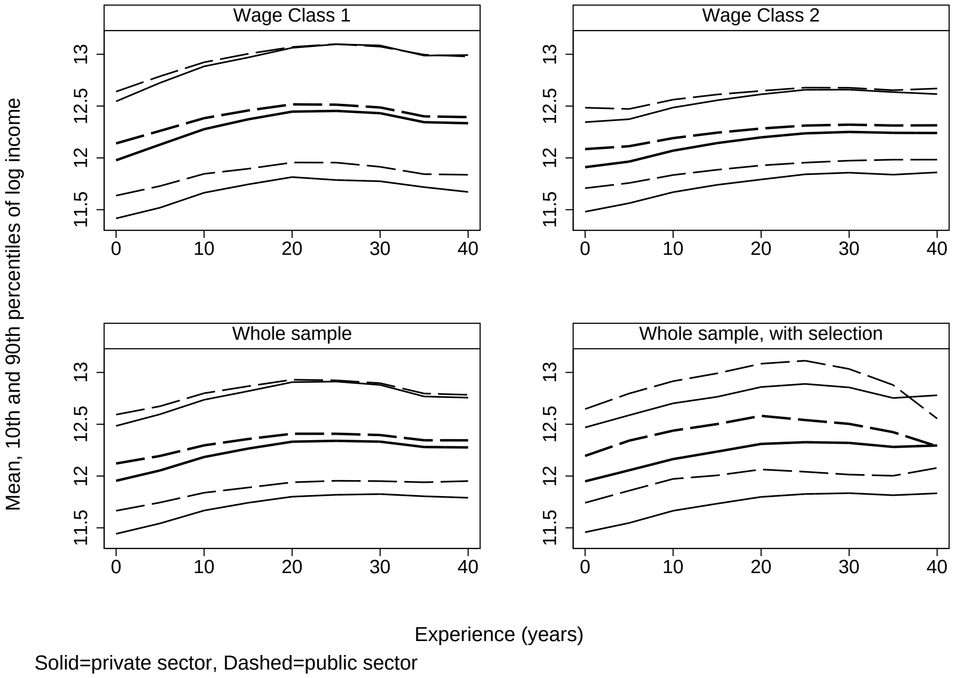

Figure 10: **Spain**: Earnings-Experience Profiles, all and by earnings class

11.5 *Estimation Results*

		Whole Sample			Whole sample, with selection		
		Private	Public	Difference	Private	Public	Difference
Germany	mean	8.43	8.41	−0.02	8.43	8.47	0.04*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	std. dev	0.32	0.29	−0.03*	0.32	0.28	−0.04*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	auto-cov	0.85	0.86	0.01	0.85	0.87	0.02
		(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
	returns to exp	0.04	0.09	0.05*	0.03	0.08	0.05*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	job loss rate	0.08	0.10	0.03§	0.07	0.04	−0.03*
		(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Netherlands	mean	8.69	8.65	−0.04§	8.67	8.76	0.09*
		(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
	std. dev	0.27	0.21	−0.05*	0.27	0.22	−0.05*
		(0.01)	(0.01)	(0.02)	(0.00)	(0.01)	(0.02)
	auto-cov	0.90	0.90	0.01	0.90	0.91	0.01
		(0.01)	(0.04)	(0.04)	(0.01)	(0.01)	(0.04)
	returns to exp	0.11	0.13	0.01	0.12	0.10	−0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	job loss rate	0.03	0.01	−0.02	0.02	0.01	−0.00
		(0.01)	(0.03)	(0.04)	(0.00)	(0.00)	(0.00)
France	mean	9.37	9.40	0.03§	9.36	9.49	0.13*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
	std. dev	0.32	0.30	−0.02	0.32	0.31	−0.02
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	auto-cov	0.87	0.89	0.02	0.87	0.90	0.03
		(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)
	returns to exp	0.17	0.19	0.02	0.16	0.17	0.01
		(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
	job loss rate	0.05	0.04	−0.01	0.04	0.02	−0.02*
		(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
Italy	mean	7.90	7.94	0.04*	7.91	8.03	0.12*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	std. dev	0.25	0.25	0.00	0.25	0.25	0.00
		(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
	auto-cov	0.77	0.82	0.05#	0.77	0.83	0.06*
		(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
	returns to exp	0.12	0.05	−0.06*	0.10	0.04	−0.06*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	job loss rate	0.12	0.12	0.00	0.04	0.02	−0.02*
		(0.01)	(0.03)	(0.04)	(0.00)	(0.00)	(0.00)
Spain	mean	12.20	12.30	0.11*	12.21	12.47	0.26*
		(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)
	std. dev	0.36	0.30	−0.05#	0.35	0.32	−0.03
		(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)
	auto-cov	0.77	0.80	0.03	0.77	0.83	0.06
		(0.02)	(0.09)	(0.10)	(0.02)	(0.07)	(0.07)
	returns to exp	0.18	0.14	−0.04	0.16	0.13	−0.03
		(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
	job loss rate	0.12	0.10	−0.02	0.07	0.03	−0.04*
		(0.01)	(0.02)	(0.03)	(0.00)	(0.01)	(0.01)
UK	mean	7.41	7.44	0.03#	7.42	7.50	0.09*
		(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
	std. dev	0.38	0.34	−0.04§	0.39	0.35	−0.04§
		(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
	auto-cov	0.83	0.88	0.05	0.83	0.88	0.06
		(0.01)	(0.04)	(0.04)	(0.01)	(0.03)	(0.03)
	returns to exp	0.15	0.15	0.00	0.14	0.13	−0.01
		(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
	job loss rate	0.05	0.03	−0.02	0.04	0.02	−0.01§
		(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)

Notes: Bootstrapped standard errors in parenthesis. * $p<0.01$, § $p<0.05$, # $p<0.10$.

Table 26: Cross-sectional earnings and job loss differences

		Whole Sample			Whole sample, with selection		
		10th	**50th**	**90th**	**10th**	**50th**	**90th**
Germany	Lifetime Value	4.95	0.57	−2.22	8.11∗	5.23∗	3.52
		(3.08)	(1.98)	(2.03)	(3.09)	(1.88)	(2.17)
	Wage	−0.73	−3.20§	−5.33∗	8.13∗	4.45∗	2.85
		(2.27)	(1.54)	(1.76)	(2.08)	(1.36)	(1.91)
Netherlands	Lifetime Value	3.54	−1.31	−5.09§	7.97§	6.18∗	3.43
		(3.95)	(2.58)	(2.23)	(3.56)	(2.14)	(2.26)
	Wage	−0.23	−2.97	−8.69∗	10.99∗	9.80∗	5.73∗
		(2.98)	(2.00)	(1.99)	(2.22)	(1.50)	(2.18)
France	Lifetime Value	9.05∗	5.69∗	3.10	13.47∗	12.92∗	11.22∗
		(3.24)	(1.99)	(2.23)	(3.73)	(2.64)	(2.84)
	Wage	3.96#	2.87#	1.31	13.20∗	12.60∗	12.99∗
		(2.16)	(1.59)	(2.21)	(2.33)	(2.04)	(2.94)
Italy	Lifetime Value	−1.87	0.25	2.29	0.48	4.21#	15.30∗
		(1.65)	(1.05)	(1.63)	(2.21)	(1.62)	(2.91)
	Wage	7.84∗	3.66∗	2.24	12.50∗	11.35∗	14.62∗
		(1.57)	(1.01)	(1.55)	(1.25)	(1.14)	(2.23)
Spain	Lifetime Value	8.45§	7.17#	4.73	21.74∗	26.52∗	21.04∗
		(3.43)	(3.86)	(3.94)	(3.47)	(2.87)	(3.60)
	Wage	17.67∗	10.90∗	4.60	31.44∗	28.42∗	23.80∗
		(4.43)	(3.51)	(3.99)	(2.92)	(2.26)	(2.93)
UK	Lifetime Value	0.53	1.06	0.52	8.35#	3.84	2.52
		(4.40)	(2.45)	(2.88)	(4.97)	(2.68)	(2.87)
	Wage	7.07§	3.95§	−0.96	14.49∗	9.51∗	3.24
		(3.13)	(2.02)	(2.48)	(3.25)	(2.31)	(2.67)

Notes: Bootstrapped standard errors in parenthesis. * $p<0.01$, § $p<0.05$, # $p<0.10$.

Table 27: Public premia (log points) in Lifetime Values and Wages, selected percentiles of the distribution

	Whole sample			Whole sample, with selection		
	Private	**Public**	**Difference**	**Private**	**Public**	**Difference**
Germany						
Lifetime Value mean	11.25	11.26	0.01	11.25	11.30	0.05*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
std. dev.	0.36	0.33	−0.03§	0.36	0.34	−0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wage mean	8.40	8.37	−0.03§	8.40	8.45	0.05*
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
std. dev.	0.32	0.29	−0.03*	0.32	0.29	−0.04*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Netherlands						
Lifetime Value mean	11.52	11.51	−0.01	11.50	11.56	0.06§
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
std. dev.	0.33	0.30	−0.04*	0.33	0.31	−0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wage mean	8.67	8.63	−0.04§	8.66	8.75	0.09*
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
std. dev.	0.27	0.21	−0.05*	0.27	0.22	−0.05*
	(0.00)	(0.01)	(0.02)	(0.00)	(0.01)	(0.02)
France						
Lifetime Value mean	12.21	12.27	0.06*	12.19	12.31	0.13*
	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)
std. dev.	0.42	0.40	−0.02	0.42	0.41	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wage mean	9.34	9.37	0.03#	9.34	9.47	0.13*
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
std. dev.	0.32	0.30	−0.02	0.32	0.30	−0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Italy						
Lifetime Value mean	10.75	10.75	0.00	10.71	10.77	0.06*
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
std. dev.	0.28	0.29	0.01#	0.28	0.32	0.04*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wage mean	7.87	7.91	0.04*	7.90	8.02	0.12*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
std. dev.	0.25	0.25	0.00	0.25	0.25	0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Spain						
Lifetime Value mean	15.14	15.21	0.07§	15.10	15.34	0.24*
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
std. dev.	0.38	0.37	−0.02	0.38	0.38	−0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Wage mean	12.15	12.26	0.11*	12.18	12.46	0.28*
	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)
std. dev.	0.35	0.30	−0.05	0.35	0.32	−0.02
	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)
UK						
Lifetime Value mean	10.25	10.26	0.01	10.25	10.29	0.04
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
std. dev.	0.38	0.38	−0.00	0.38	0.37	−0.02
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Wage mean	7.38	7.42	0.04#	7.39	7.49	0.09*
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
std. dev.	0.38	0.34	−0.04§	0.39	0.35	−0.04§
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)

Notes: Bootstrapped standard errors in parenthesis. * p<0.01, § p<0.05, # p<0.10.

Table 28: Public premia in (log) Lifetime Values and (log) Wages

APPENDIX

A Attrition by Country

As outlined in section 4.2 there is some attrition from the sample for each country, which we assume exogenous. Some of the attrition is a result of our sample selection rules in which an individual is considered censored from the first time that they have a gap in their response history. The table below shows the extent of attrition in each sample, after 4 years and after 7 years and the proportion of individuals who are censored because of a gap in their response history:

	Germany	Neth.	France	Italy	Spain
% of initial sample remaining at year 5	87.6	86.0	75.0	84.2	82.5
% of initial sample remaining at year 8	57.0	51.4	40.4	47.6	49.2
% of attritting individuals due to gap in responses	5.3	5.3	19.8	8.5	8.2

Table A-1: Sample Attrition by Country

B Education Breakdown by Country

	Germany	Neth.	France	Italy	Spain
Education Level	%	%	%	%	%
"high"	28.8	25.1	27.1	10.6	33.0
"medium"	60.3	54.2	44.3	49.5	24.1
"low"	10.9	20.7	28.6	39.9	42.9
Total	100.0	100.0	100.0	100.0	100.0

Table B-1: Education Breakdown by Country

"High" education refers to ISCED levels 5-7, corresponding to any tertiary level education. "Medium" level education refers to ISCED level 3 and corresponds to upper-secondary (i.e. post-compulsory) level schooling, while "low" education refers to ISCED levels 0-2 and represents levels of education up to the end of compulsory (secondary) school. We can see from the table that for Germany, the Netherlands, France and Spain the proportion of "high" educated individuals is of a similar order of magnitude, however Italy has a considerably smaller proportion of individuals in the top educated bracket. As the ECHP surveys are designed to be the same in each country and the education coding is a standard international classification, this should be reflecting genuine differences in educational composition of each sample. Ideally the proportion with "high" education would approximately similar in each country, which is not the case, primarily due to Italy. An alternative strategy would be to capture human capital differences via occupational classification. The ECHP contains the International Standard Classification of Occupation (ISCO-88) 1-digit level classification for individual's occupations. The 1-digit ISCO-88 classification assigns occupations to one of 9 categories, from 1 "Legislators, senior officials, managers", through 5 "Service workers and shop and market sales workers", to 9 "Elementary occupations". Attempts to combine these gradings into 3 broad levels of human capital attainment, that would result in similar proportions of individuals at each level in each country, were unsuccessful. As a consequence, though dividing individuals according to the 3 category education variable does not result in absolute symmetry across countries, it is more satisfactory than the possible alternative human capital measures based on occupational classification.

C Job state transitions by unobserved mobility class

In the tables below we reproduce the Observed and Predicted job state transition matrices from Tables 16 to 20 (upper panel) and show these matrices separately by mobility class (lower panel). This is to illustrate that for each unobserved mobility class, there are job state transitions in every direction, allowing us to identify the model coefficients for movement between states for the different types of worker.

	Observed			Predicted, all			
state at $t-1$	state at t			state at t			
↓	private	public	unemp.	private	public	unemp.	
Private	93.1	1.2	5.6	94.4	1.2	4.3	Max distance: 7.6
Public	7.0	89.6	3.2	7.4	89.8	2.6	Max distance, 2x2: 1.3
Unemp.	32.7	5.1	62.1	38.7	6.6	54.5	

	Predicted, $k^m = 1$			Predicted, $k^m = 2$		
state at $t-1$	state at t			state at t		
↓	private	public	unemp.	private	public	unemp.
Private	78.5	2.3	19.1	97.3	0.5	2.1
Public	16.0	61.3	22.6	55.0	43.8	1.1
Unemp.	24.8	5.6	69.4	77.5	3.1	19.2

	Predicted, $k^m = 3$		
state at $t-1$	state at t		
↓	private	public	unemp.
Private	90.6	9.0	0.2
Public	5.9	93.3	0.7
Unemp.	48.4	47.9	3.5

Table C-1: **Germany**: Fit to Job Mobility Data, by Mobility Class

	Observed			Predicted, all			
state at $t-1$	state at t			state at t			
↓	private	public	unemp.	private	public	unemp.	
Private	95.9	2.0	1.9	96.3	2.1	1.4	Max distance: 5.5
Public	8.5	89.8	1.5	7.7	91.4	0.8	Max distance, 2x2: 1.6
Unemp.	28.2	4.5	67.2	32.1	6.1	61.7	

	Predicted, $k^m = 1$			Predicted, $k^m = 2$		
state at $t-1$	state at t			state at t		
↓	private	public	unemp.	private	public	unemp.
Private	74.9	21.0	3.9	98.1	0.8	1.0
Public	6.3	92.6	0.9	77.3	22.6	0.0
Unemp.	21.1	9.0	69.8	55.4	0.6	43.9

Table C-2: **Netherlands**: Fit to Job Mobility Data, by Mobility Class

state at $t-1$	Observed			Predicted, all			
	state at t			state at t			
$\downarrow$	private	public	unemp.	private	public	unemp.	
Private	95.5	0.4	4.0	96.7	0.3	2.8	Max distance: 3.1
Public	0.9	96.8	2.1	0.9	97.6	1.3	Max distance, 2x2: 1.2
Unemp.	29.8	7.4	62.6	32.1	8.2	59.5	

state at $t-1$	Predicted, $k^m = 1$			Predicted, $k^m = 2$		
	state at t			state at t		
$\downarrow$	private	public	unemp.	private	public	unemp.
Private	98.8	0.3	0.8	88.4	0.6	10.9
Public	1.2	98.3	0.4	0.5	90.4	9.0
Unemp.	71.2	12.5	16.1	31.7	8.4	59.8

Table C-3: **France**: Fit to Job Mobility Data, by Mobility Class

state at $t-1$	Observed			Predicted, all			
	state at t			state at t			
$\downarrow$	private	public	unemp.	private	public	unemp.	
Private	94.9	1.5	3.5	96.1	1.6	2.2	Max distance: 4.3
Public	5.3	93.0	1.6	5.1	93.8	1.0	Max distance, 2x2: 1.2
Unemp.	18.4	3.3	78.2	21.3	4.7	73.9	

state at $t-1$	Predicted, $k^m = 1$			Predicted, $k^m = 2$		
	state at t			state at t		
$\downarrow$	private	public	unemp.	private	public	unemp.
Private	85.4	1.6	12.9	97.3	2.0	0.6
Public	3.4	89.5	7.9	4.9	94.7	0.3
Unemp.	11.8	3.3	84.8	50.4	9.9	39.5

state at $t-1$	Predicted, $k^m = 3$		
	state at t		
$\downarrow$	private	public	unemp.
Private	94.4	1.0	4.4
Public	6.9	90.0	2.9
Unemp.	20.7	2.8	76.4

Table C-4: **Italy**: Fit to Job Mobility Data, by Mobility Class

	Observed			Predicted, all			
state at $t-1$	state at t			state at t			
$\downarrow$	private	public	unemp.	private	public	unemp.	
Private	92.0	1.4	6.4	93.4	1.7	4.8	Max distance: 5.6
Public	8.3	88.1	3.5	9.2	88.1	2.5	Max distance, 2x2: 1.4
Unemp.	32.6	3.6	63.7	37.0	4.8	58.1	

	Predicted, $k^m = 1$			Predicted, $k^m = 2$		
state at $t-1$	state at t			state at t		
$\downarrow$	private	public	unemp.	private	public	unemp.
Private	74.9	20.4	4.5	96.8	0.6	2.4
Public	5.3	92.9	1.7	70.3	29.3	0.3
Unemp.	35.7	29.7	34.5	66.9	0.9	32.0

	Predicted, $k^m = 3$		
state at $t-1$	state at t		
$\downarrow$	private	public	unemp.
Private	82.6	3.2	14.0
Public	25.6	61.1	13.1
Unemp.	27.0	4.3	68.6

Table C-5: **Spain**: Fit to Job Mobility Data, by Mobility Class

D Evolution of the Labour Market

We now briefly illustrate the evolution of the labour market in each country over the time of our data. Figures D.1 to D.5 show the male unemployment rate[26] for the years 1991-2001 (top panel), thus covering the three years preceding our sample as well as the sample years themselves, and the public sector share of total employment for our sample (bottom panel).

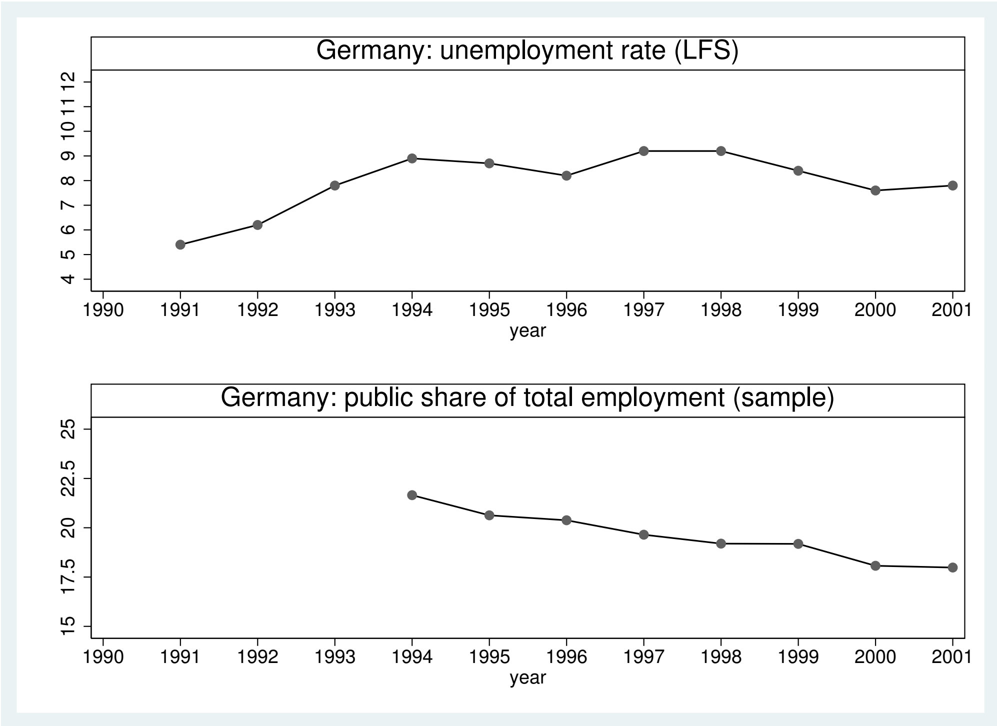

Figure D.1: **Germany**: Unemployment rate, males, 1991-2001, and Sample public sector share

For Germany, both the unemployment rate and the public share of employment are reasonably stable over the time of our sample, the unemployment rate rising in the early nineties before levelling out at around 9% from 1994 onwards. The public sector share of total employment falls slowly from around 21% at the start of the sample to 18% by 2001.

The unemployment rate in the Netherlands is steady at around 5-6% prior to the start of the sample period in 1994, but then falls gradually over the following years to be around 3% in 2001. The public sector share of total employment remains largely stable in the sample, though falling steadily from 24% in 1994 to just under 21% in 2001.

[26]For each country the unemployment rate is calculated using data from the Labour Force Survey.

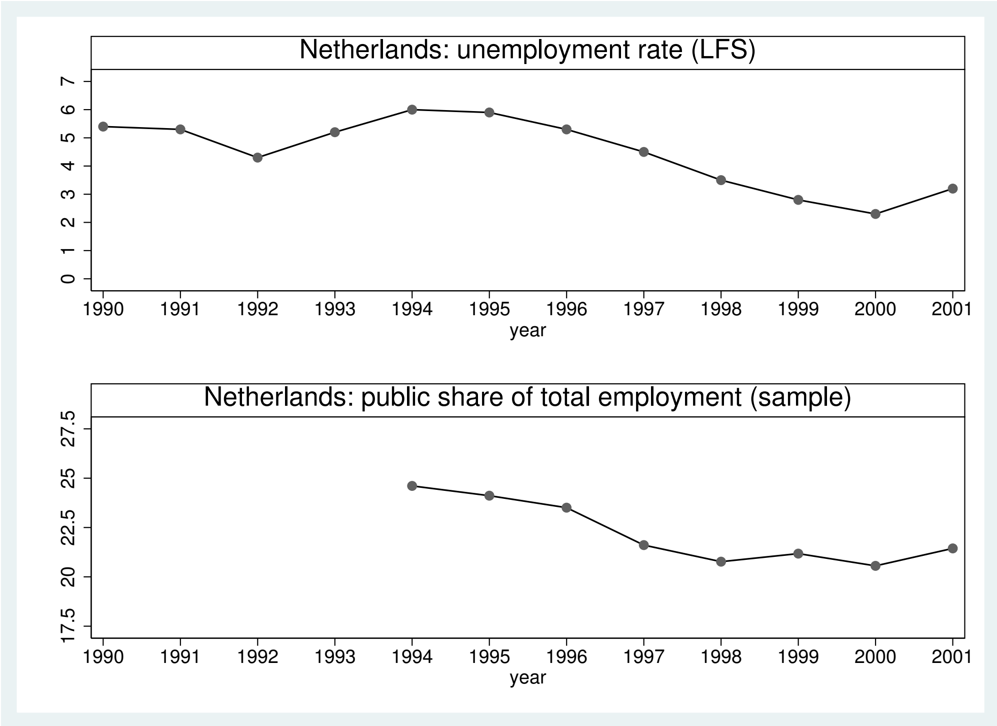

Figure D.2: **Netherlands**: Unemployment rate, males, 1991-2001, and Sample public sector share

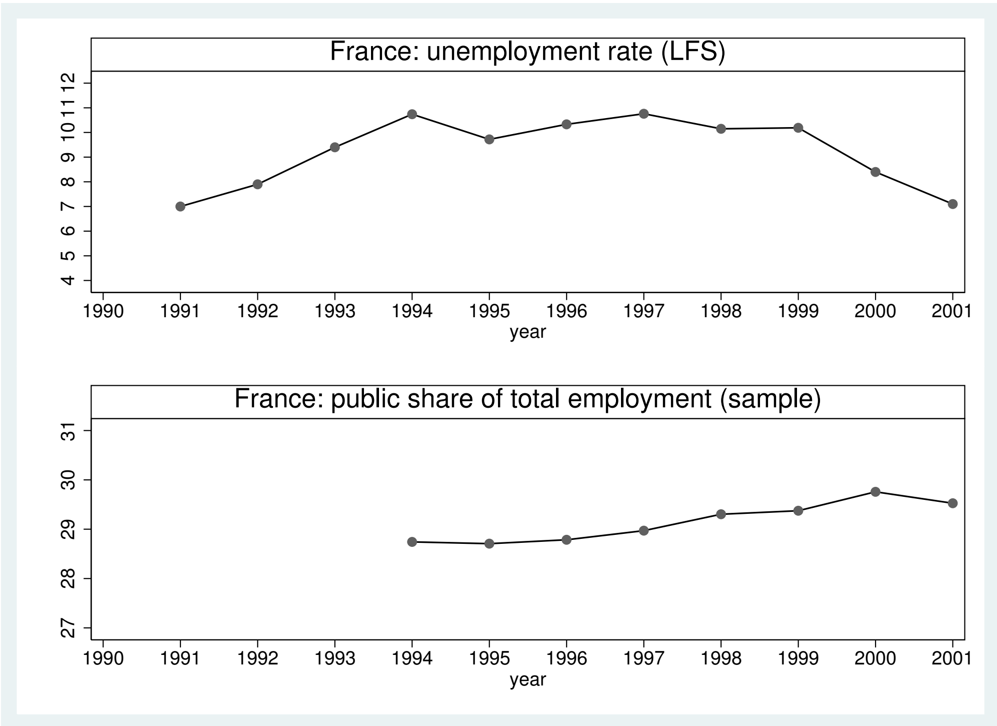

Figure D.3: **France**: Unemployment rate, males, 1991-2001, and Sample public sector share

In France the unemployment rate was rising steadily from 7% in 1991 to almost 11% by 1994 and the start of our sample. During the sample period the unemployment rate remains largely stable around 10% before slightly dropping down towards the end of the millennium. The public share of total employment however remains almost totally constant through the sample time frame, 29% to the nearest percent in each year.

As Figure D.4 shows, the unemployment rate is largely stable for Italy at around 7.5% for the years preceding

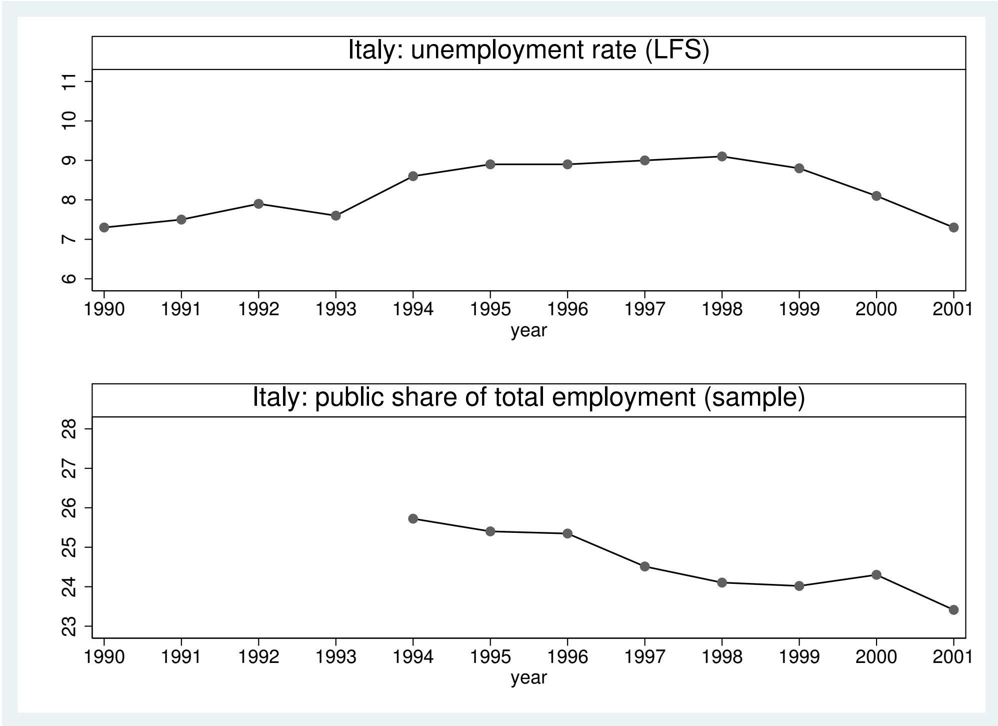

Figure D.4: **Italy**: Unemployment rate, males, 1991-2001, and Sample public sector share

our sample period before rising to just over 8.5% in 1994 and remaining around this level throughout the majority of the sample before declining back down towards 7.5% in the final years of the sample. The public share of total employment in the sample remains almost constant, declining slightly over the sample period from around 26% in 1994 to 23% in 2001.

For Spain, in the years leading up to the start of the sample in 1994, the unemployment rate in Spain was rising quite sharply from around 12% in 1990 to almost 20% in 1994. During the course of the sample however, unemployment falls steadily and is down to 7.5% by 2001. The public sector share of total employment is stable at around 19% for the first three years of our sample before dropping slightly in 1997 (to 17.5%) and then falling slightly further to 16% in 2001.

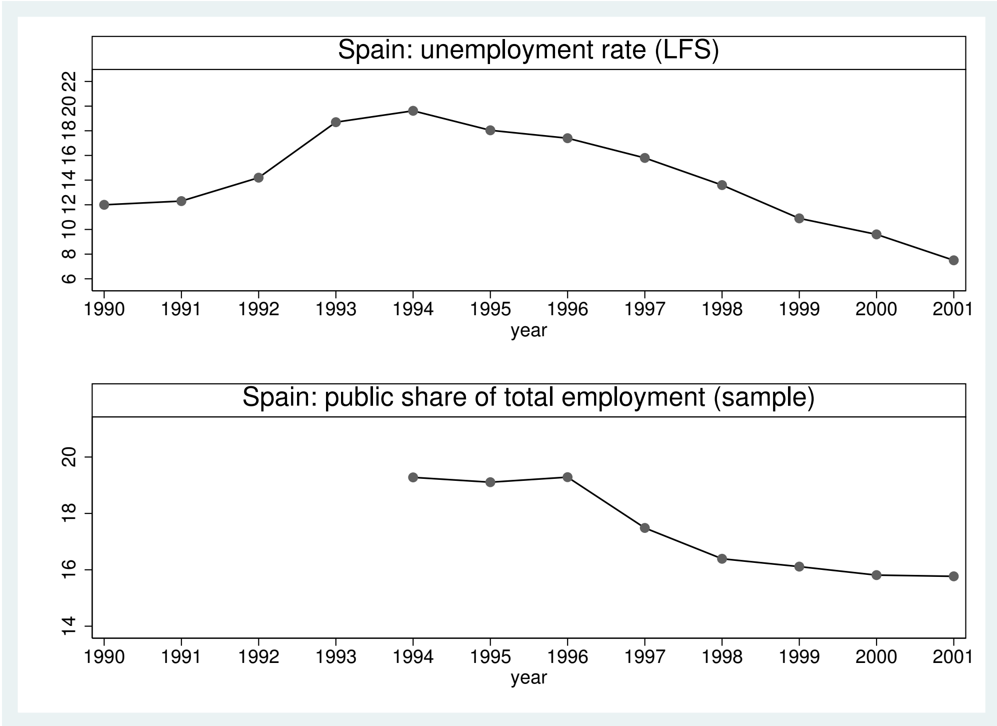

Figure D.5: **Spain**: Unemployment rate, males, 1991-2001, and Sample public sector share

E Model Specification

In this appendix we describe in full detail the functional form assumptions of the model. To refresh the notation and basic structure of the statistical model: each country's sample is a set of N workers indexed i =1, . . . , N, each of whom is followed over T_i consecutive years. A typical individual observation i is a vector $\mathbf{x}_i = \left(\mathbf{y}_i, \mathbf{e}_i, \mathbf{pub}_i, \mathbf{z}_i^v, z_i^f\right)$, to which we append a pair of unobserved class indexes, $k_i = (k_i^m, k_i^y)$. As outlined in Section 5 of the main body, there are three components to individual i's contribution to the complete likelihood (equation (1)), referring respectively to unobserved heterogeneity, labour market status history and earnings history. Below we set out the full specification of each of these components. The choice of covariates to be included in each component was informed not only by the descriptive analysis of section 4, but also by a concern for numerical tractability, parsimony and the aim to get as close as possible to estimating the same model specification for each of the countries.

E.1 Unobserved Heterogeneity

As outlined in equation (2), the attachment of individual i to a given latent class $k_i = (k_i^m, k_i^y)$ is modelled as the product of two terms: $\ell_i\left(k_i \mid z_i^f\right) = \Pr\left\{k_i^y \mid k_i^m, z_i^f\right\} \cdot \Pr\left\{k_i^m \mid z_i^f\right\}$, which are both specified as multinomial logits:

$$\Pr\left\{k_i^m = k^m \mid z_i^f\right\} = \frac{\exp\left(z_i^{f\prime} \cdot \kappa_{k^m}^m\right)}{\sum_{k=1}^{K^m} \exp\left(z_i^{f\prime} \cdot \kappa_k^m\right)} \quad \text{and} \quad \Pr\left\{k_i^y \mid k_i^m, z_i^f\right\} = \frac{\exp\left[\begin{pmatrix} z_i^f \\ k_i^m \end{pmatrix}' \cdot \kappa_{k^y}^y\right]}{\sum_{k=1}^{K^y} \exp\left[\begin{pmatrix} z_i^f \\ k_i^m \end{pmatrix}' \cdot \kappa_k^y\right]}, \tag{E1}$$

where κ_1^m and κ_1^y are both normalised at zero.

E.2 Labour Market States

Equations (3), (4) and (5) established that the individual labour market histories contribute to the complete likelihood as:

$$\ell_i\left(\mathbf{S}_i \mid \mathbf{z}_i^v, z_i^f, k_i^m\right) = \Pr\left\{S_{i1} \mid z_i^f, k_i^m\right\} \times \prod_{t=2}^{T_i} \Pr\left\{S_{it} \mid S_{i,t-1}, z_{i,t-1}^v, z_i^f, k_i^m\right\}, \tag{E2}$$

We can express this rather in terms of the indicator variables e_{it} and pub_{it} as:

$$\begin{aligned}\ell_i\left(\mathbf{e}_i, \mathbf{pub}_i \mid \mathbf{z}_i^v, z_i^f, k_i^m\right) &= \Pr\left\{e_{i1} \mid z_i^f, k_i^m\right\} \times \left[\Pr\left\{\text{pub}_{i1} \mid z_i^f, k_i^m\right\}\right]^{e_{it}} \\ &\times \prod_{t=2}^{T_i}\left(\Pr\left\{e_{it} \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{i,t-1}^v, z_i^f, k_i^m\right\} \times \left[\Pr\left\{\text{pub}_{it} \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{i,t-1}^v, z_i^f, k_i^m\right\}\right]^{e_{it}}\right).\end{aligned} \tag{E3}$$

As alluded to in subsection (5.3), each component is specified as a logit. Allowing $\Lambda(x) = \left(1 + e^{-x}\right)^{-1}$ to designate the logistic cdf:

$$\begin{aligned}\Pr\left\{e_{it} \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{i,t-1}^v, z_i^f, k_i^m\right\} &= \Lambda\left(\left[e_{i,t-1}, \text{pub}_{i,t-1}, z_{i,t-1}^v{}', z_i^f{}', k_i^m{}'\right] \cdot \psi\right), \\ \Pr\left\{\text{pub}_{it} \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{i,t-1}^v, z_i^f, k_i^m\right\} &= \Lambda\left(\left[e_{i,t-1}, \text{pub}_{i,t-1}, z_{i,t-1}^v{}', z_i^f{}', k_i^m{}'\right] \cdot \chi\right),\end{aligned} \tag{E4}$$

We allow the unobserved mobility heterogeneity class k_i^m to affect the unemployment and public sector probabilities only through altering the constant terms in the respective logits. This is because the number of observed sector transitions is not sufficient in the sample for most of the countries to allow less restrictive specifications – such as allowing this unobserved class to interact with experience or education – to be estimated. However, where possible (Germany, Italy, Spain) we do allow the effect of experience to interact with previous state.[27] For the initial job state probabilities, we use similar specifications[28]:

$$\Pr\left\{e_{i1} \mid z_i^f, k_i^m\right\} = \Lambda\left(\left[z_i^f{}', k_i^m{}'\right] \cdot \psi_0\right) \text{ and } \Pr\left\{\text{pub}_{i1} \mid z_i^f, k_i^m\right\} = \Lambda\left(\left[z_i^f{}', k_i^m{}'\right] \cdot \chi_0\right) \tag{E5}$$

E.3 Earnings

As the exposition in the main body text Section (5.4) details much of the modelling of earnings trajectories, what remains for this appendix is to set out the set of functions $\{\mu(\cdot), \sigma(\cdot), \tau_1(\cdot) \text{ and } \tau_2(\cdot)\}$ introduced in equations (7) and (9). Recall from Section (5.4) that only individuals who are employed at date-t have earnings information available at date-t, therefore $e_{it} = 1$ for all observations used to estimate the $\mu(\cdot)$, and indeed the $\sigma(\cdot)$ function, and as such e_{it} is not an argument of either function. Starting with $\mu(\cdot)$, we posit that:

$$\mu\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right) = \begin{bmatrix} z_i^f \\ e_{i,t-1}\end{bmatrix}' \mu_0 + \left[z_{it}^v * \text{pub}_{it}\right]' \mu_1 + \left[k_i^y * z_{it}^v\right]' \mu_2 + \left[k_i^y \cdot \text{pub}_{it}\right] \mu_3, \tag{E6}$$

where the notation $x * y$ stands for all of the main effects and interactions of variables x and y, and $x \cdot y$ stands for the single interaction term between x and y. Thus the specification of the $\mu(\cdot)$ function allows the effect of experience to differ across job sectors and wage classes, and the public sector effect is also allowed to vary with wage class. Previous period unemployment and time-invariant heterogeneity can affect the intercept only.

Turning to the log earnings variance function, we specify:

$$\sigma\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^v, k_i^y\right) = \sqrt{\exp\left(\begin{bmatrix} z_{it}^v \\ \text{pub}_{it} \\ e_{i,t-1} \\ k_i^y\end{bmatrix}' \cdot \sigma_0\right)}. \tag{E7}$$

[27] In the Netherlands and France there is not sufficient movement between sectors to allow the interaction of experience and previous state to be estimated accurately, moreover in France the education dummies are insignificant and so in the interests of parsimony are dropped.

[28] Again the unobserved mobility heterogeneity class k_i^m can only alter the constant term in each equation, and for the initial states we do not allow interactions of experience with previous state

Clearly the functional form posited for $\sigma(\cdot)$ is considerably more restrictive than we allow for the earnings means. Specifically we do not include the time-invariant observed individual characteristics z_i^f amongst the arguments of $\sigma(\cdot)$, thus we allow them to influence earnings variance only through their link to the time-invariant wage class, k_i^y. Moreover, we do not allow interactions of the wage class with any of the other arguments. Given the relatively small sample sizes available, and some experimentation with allowing some interactions, between for example k_i^y and pub_{it}, we find this specification to provide the best fit for all of the countries in the data. Note that by specifying it as an exponential, we force the log earnings variance to be positive.

Finally, we come to the specification of the earnings dynamics, which are governed by the functions $\tau_1(\cdot)$ and $\tau_2(\cdot)$. Again recall that earnings at date-t are only available for individuals in employment at that date and therefore $e_{it} = 1$ and $e_{i,t-1} = 1$ for all observations contributing to the estimation of the $\tau_1(\cdot)$ function and as such are not arguments of the function. The first-order auto-correlation of earnings, $\tau_1(\cdot)$, is posited as:

$$\tau_1\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right) = -1 + 2 \cdot \Lambda \left\{ \left[\begin{pmatrix} z_{it}^f \\ z_{it}^v \\ \text{pub}_{it} \\ \text{pub}_{i,t-1} \end{pmatrix} \cdot k_i^y \right]' \cdot \zeta_0 \right\}. \tag{E8}$$

This specification requires some clarification. Firstly, the transformation $-1 + 2 \cdot \Lambda(\cdot)$ which we apply to a linear index in the explanatory variables is there to constrain $\tau_1(\cdot)$, which is a correlation coefficient, to lie within $[-1, +1]$. Second, as with the specification of $\sigma(\cdot)$ function, the number of interactions amongst the covariates is limited to allowing different impacts of each covariate depending on the wage class. This specification was decided upon following numerous trials involving different specifications with various interactions permitted. The finding was that the vast increase in computation time that this entailed for each country, did not bring any clear benefit in terms of greater precision of the fit, thus the current more parsimonious specification was settled upon.

The correlation between normalised log earnings and normalised log earnings lagged twice, $\tau_2(\cdot)$, is more complex. First let us recall the notation introduced in Section 5.4's equation (9), for the one- and two-lag autocorrelations of earnings at date-t:

$$\begin{aligned} \tau_{i,t,t-1} &= \tau_1\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right) \\ \text{and} \quad \tau_{i,t,t-2} &= \tau_2\left(\text{pub}_{it}, \text{pub}_{i,t-1}, \text{pub}_{i,t-2}, z_{it}^v, z_i^f, k_i^y\right). \end{aligned}$$

Now we write:

$$\begin{aligned} \tau_2\left(\text{pub}_{it}, \text{pub}_{i,t-1}, \text{pub}_{i,t-2}, z_{it}^v, z_i^f, k_i^y\right) &= \tau_{i,t,t-1} \cdot \tau_{i,t-1,t-2} \\ &+ \left[\sqrt{\left(1 - \tau_{i,t,t-1}^2\right) \cdot \left(1 - \tau_{i,t-1,t-2}^2\right)}\right] \cdot \widetilde{\tau}_2\left(k_i^y\right), \end{aligned} \tag{E9}$$

with $\widetilde{\tau}_2\left(k_i^y\right) = -1 + 2 \cdot \Lambda\left(k_i^{y\prime} \cdot \xi\right)$ simply specified as an wage class-specific constant within $[-1, +1]$. Note that $\tau_{i,t-1,t-2}$ is simply the first lag of $\tau_{i,t,t-1}$.

These latter equations require some comments. Firstly, we have to constrain $\tau_2(\cdot)$ in such a way that, given $\tau_{i,t,t-1}$ and $\tau_{i,t-1,t-2}$, the matrix:

$$\underline{\tau}_{it}^{(3)} = \begin{pmatrix} 1 & \tau_{i,t,t-1} & \tau_{i,t,t-2} \\ \tau_{i,t,t-1} & 1 & \tau_{i,t-1,t-2} \\ \tau_{i,t,t-2} & \tau_{i,t-1,t-2} & 1 \end{pmatrix}$$

is a consistent covariance matrix. This is the case provided that its determinant Δ_{it} is positive (and that the various τ's lie in $[-1, +1]$). Δ_{it} is defined by $\Delta_{it} = 1 - \tau_{i,t,t-1}^2 - \tau_{i,t-1,t-2}^2 - \tau_{i,t,t-2}^2 + 2\tau_{i,t,t-1}\tau_{i,t-1,t-2}\tau_{i,t,t-2}$. Solving for

$\tau_{i,t,t-2}$, we get:

$$\tau_{i,t,t-2} = \tau_{i,t,t-1} \cdot \tau_{i,t-1,t-2} \pm \sqrt{\left(1-\tau_{i,t,t-1}^2\right) \cdot \left(1-\tau_{i,t-1,t-2}^2\right) - \Delta_{it}}. \tag{E10}$$

Because Δ_{it} is positive, $\tau_{i,t,t-2}$ has to stay within the interval

$$\left[\tau_{i,t,t-1} \cdot \tau_{i,t-1,t-2} - \sqrt{\left(1-\tau_{i,t,t-1}^2\right) \cdot \left(1-\tau_{i,t-1,t-2}^2\right)}, \tau_{i,t,t-1} \cdot \tau_{i,t-1,t-2} + \sqrt{\left(1-\tau_{i,t,t-1}^2\right) \cdot \left(1-\tau_{i,t-1,t-2}^2\right)}\right].$$

This is achieved by the parameterization in equation (E9) given the constraint $\widetilde{\tau}_2(\cdot) \in [-1,+1]$.

E.4 Derivation of the Likelihood of Earnings Trajectory

From equation (6) and as a consequence of our assumption of a second-order Markov process for individual earnings (omitting the individual i index and the conditioning variables), we have, for individuals with three consecutive data points on income:

$$\ell(\mathbf{y}) = \ell(y_2, y_1) \cdot \prod_{t=3}^{T} \ell(y_t \mid y_{t-1}, y_{t-2}) = \ell(y_2, y_1) \cdot \prod_{t=3}^{T} \frac{\ell(y_t, y_{t-1}, y_{t-2})}{\ell(y_{t-1}, y_{t-2})}. \tag{E11}$$

Each term in this expression can be written as a joint density of a triple or a pair of normalised log-earnings, $\widetilde{y}_{it} = \frac{y_{it}-\mu_{it}}{\sigma_{it}}$:

$$\begin{aligned}
\ell(y_t, y_{t-1}, y_{t-2}) &= \frac{1}{\sigma_t \sigma_{t-1} \sigma_{t-2}} \cdot \varphi_3\left(\widetilde{y}_t, \widetilde{y}_{t-1}, \widetilde{y}_{t-2}; \underline{\tau}_t^{(3)}\right) \\
\ell(y_t, y_{t-1}) &= \frac{1}{\sigma_t \sigma_{t-1}} \cdot \varphi_2\left(\widetilde{y}_t, \widetilde{y}_{t-1}; \underline{\tau}_t^{(2)}\right)
\end{aligned}$$

So the likelihood of an earning trajectory becomes:

$$\begin{aligned}
\ell(\mathbf{y}) &= \frac{1}{\sigma_1 \sigma_2} \cdot \varphi_2\left(\widetilde{y}_2, \widetilde{y}_1; \underline{\tau}_2^{(2)}\right) \cdot \prod_{t=3}^{T} \frac{\varphi_3\left(\widetilde{y}_t, \widetilde{y}_{t-1}, \widetilde{y}_{t-2}; \underline{\tau}_t^{(3)}\right)}{\varphi_2\left(\widetilde{y}_{t-1}, \widetilde{y}_{t-2}; \underline{\tau}_{t-1}^{(2)}\right)} \cdot \left(\prod_{t=3}^{T} \frac{1}{\sigma_t}\right) \\
&= \left(\prod_{t=1}^{T} \frac{1}{\sigma_t}\right) \cdot \frac{\varphi_2\left(\widetilde{y}_2, \widetilde{y}_1; \underline{\tau}_2^{(2)}\right) \cdot \prod_{t=3}^{T} \varphi_3\left(\widetilde{y}_t, \widetilde{y}_{t-1}, \widetilde{y}_{t-2}; \underline{\tau}_t^{(3)}\right)}{\varphi_2\left(\widetilde{y}_2, \widetilde{y}_1; \underline{\tau}_2^{(2)}\right) \cdot \prod_{t=4}^{T} \varphi_2\left(\widetilde{y}_{t-1}, \widetilde{y}_{t-2}; \underline{\tau}_{t-1}^{(2)}\right)} \\
&= \left(\prod_{t=1}^{T} \frac{1}{\sigma_t}\right) \cdot \frac{\prod_{t=3}^{T} \varphi_3\left(\widetilde{y}_t, \widetilde{y}_{t-1}, \widetilde{y}_{t-2}; \underline{\tau}_t^{(3)}\right)}{\prod_{t=3}^{T-1} \varphi_2\left(\widetilde{y}_t, \widetilde{y}_{t-1}; \underline{\tau}_t^{(2)}\right)}.
\end{aligned} \tag{E12}$$

E.5 Likelihood of Earnings Trajectory: cases with missing information

With the assumptions and notation introduced in equations (7) to (9) (in section 5.4 above), we can specify the likelihood of the typical individual's earnings trajectory $\mathbf{y}_i$ defined in equation (6) (which is restated above as equation (E11)). This will depend on the earnings information available, as we observe earnings at date-t only for those in employment. If earnings information is available at the date-t interview, then there are four possibilities regarding the presence of earnings information at the date-$t-1$ and date-$t-2$ interviews:

- Case A: date-$(t-1)$: yes; date-$(t-2)$: yes.
- Case B: date-$(t-1)$: yes; date-$(t-2)$: no.
- Case C: date-$(t-1)$: no; date-$(t-2)$: yes.
- Case D: date-$(t-1)$: no; date-$(t-2)$: no.

Which case an individual's date-t observation is will determine whether that term in the product in (6) is $\ell(y_t \mid y_{t-1}, y_{t-2})$, $\ell(y_t \mid y_{t-1})$, $\ell(y_t \mid y_{t-2})$ or simply $\ell(y_t)$.

In the complete earnings information scenario, an individual has case (A) for all $t >= 3$, that is they have earnings information not only at the date-t interview but also, $(t-1)$ **and** $(t-2)$ interviews, for all $t >= 3$. In this scenario, the equation (6) earnings trajectory simplifies neatly to become equation (10) which is formally derived above as equation (E12). However, given that in each country, individuals move between employment and unemployment through the course of the panel (indeed we would not be able to identify the mobility parameters were they not to) it is necessarily not possible that we have case A for all individuals for all $t >= 3$. In the more general case, the individual's trajectory is built from a product that cannot be captured in as elegant an expression as equation (10). In each case however the individual's earnings trajectory likelihood is built from products of uni-, bi- and tri-variate normal densities and has the general form of equation (6).

For a case (B) observation at date-t, an individual has earnings information at date-t and also at date-$(t-1)$ but **not** at date-$(t-2)$. In this case the likelihood of that observation is computed as:

$$\ell(y_t \mid y_{t-1}) = \frac{\ell(y_t, y_{t-1})}{\ell(y_{t-1})} = \frac{1}{\sigma_t} \times \frac{\varphi_2\left(\widetilde{y}_t, \widetilde{y}_{t-1}; \underline{\tau}_t^{(2)}\right)}{\varphi(\widetilde{y}_{t-1})} \tag{E13}$$

where $\varphi(.)$ is the univariate standard normal pdf and $\varphi_2\left(\cdot; \underline{\tau}^{(2)}\right)$ is the bivariate standard normal pdf with mean 0 and covariance matrix $\underline{\tau}^{(2)}$.

Similarly for a case (C) observation at date-t, an individual has earnings information at date-t and also at date-$(t-2)$ but **not** at date-$(t-1)$. In this case the likelihood of that observation is computed as:

$$\ell(y_t \mid y_{t-2}) = \frac{\ell(y_t, y_{t-2})}{\ell(y_{t-2})} = \frac{1}{\sigma_t} \times \frac{\varphi_2\left(\widetilde{y}_t, \widetilde{y}_{t-2}; \underline{\tau}_t^{(2)}\right)}{\varphi(\widetilde{y}_{t-2})} \tag{E14}$$

Finally, for a case (D) observation, the individual has earnings information only at the date-t interview, in which case the likelihood of the earnings observation is computed straightforwardly as:

$$\ell(y_t) = \frac{1}{\sigma_t} \times \varphi(\widetilde{y}_t) \tag{E15}$$

Clearly, for all individuals their first earnings observation is a case (D), and if they are observed employed in the following year that observation will be a case (B) observation.

F The EM Algorithm

In this appendix we fully detail the estimation procedure using the Expectation Maximization (EM) algorithm.

F.1 General Description

From Appendix E and the model description in Section (5) the set of parameters to be estimated can be divided into two sub-sets: the parameters relating to labour market mobility process, denoted by Θ^m, and the parameters relating to the earnings mobility process, Θ^y. The mobility process parameters are $\Theta^m = \left\{(\kappa_k^m)_{k=1}^{K^m}, \psi_0, \chi_0; \psi, \chi\right\}$ and includes all the parameters involved in equations (E1), (E4) and (E5). The earnings process parameters are $\Theta^y = \left\{(\kappa_k^y)_{k=1}^{K^y}, \mu(\cdot), \sigma(\cdot), \tau_1(\cdot), \widetilde{\tau}_2(\cdot)\right\}$, where in $\{\mu(\cdot), \sigma(\cdot), \tau_1(\cdot), \widetilde{\tau}_2(\cdot)\}$ we summarise all of the parameters of the corresponding functions, see equations (E6), (E7), (E8) and (E9).

The structure of (1) allows the individual contributions to the complete likelihood to be decomposed as
$\mathcal{L}_i(\mathbf{x}_i, k_i; \Theta^m, \Theta^y) = \mathcal{L}_i^m(\mathbf{x}_i, k_i^m; \Theta^m) \cdot \mathcal{L}_i^y(\mathbf{x}_i, k_i^m, k_i^y; \Theta^y)$, where:

$$\mathcal{L}_i^m(\mathbf{x}_i, k_i^m; \Theta^m) = \ell_i\left(\mathbf{e}_i, \mathbf{pub}_i \mid \mathbf{z}_i^v, z_i^f, k_i^m; \Theta^m\right) \cdot \Pr\left\{k_i^m \mid z_i^f; \Theta^m\right\} \tag{F1}$$

Here the dependence of the various parts of the likelihood on the sets of parameters is made explicit. This separability makes it possible to integrate earnings sequences ($\mathbf{y}_i$) and wage classes (k_i^y) out of the complete likelihood $\mathcal{L}_i(\mathbf{x}_i, k_i; \Theta^m, \Theta^y)$. This allows us to recover the parameters relating to the labour market mobility process and the mobility classes by maximising the log-likelihood of the observed job sector mobility, $\sum_{i=1}^{N} \log\left(\sum_{k_i^m=1}^{K^m} \mathcal{L}_i^m(\mathbf{x}_i, k_i^m; \Theta^m)\right)$. This maximisation can be achieved by a straightforward application of the EM algorithm for finite mixtures, described below (in sub-section F.1.1).

This first stage produces estimates of the labour market mobility parameters, which we fix at their estimated values, $\hat{\Theta}^m$, and return to the maximisation of the sample log-likelihood, $\mathcal{L}_i\left(\mathbf{x}_i, k_i; \hat{\Theta}^m, \Theta^y\right)$ but now switching attention to the earnings process component of the likelihood, $\mathcal{L}_i^y(\mathbf{x}_i, k_i^m, k_i^y; \Theta^y)$, and the relevant parameters Θ^y. Details of this part of the estimation are below (see sub-section F.1.2).

F.1.1 Estimation of the Job Mobility Parameters Θ^m

The standard EM-algorithm involves iterating two steps: the **Expectation** step and the **Maximization** step:

E-step: For an arbitrary initial value Θ_n^m of Θ^m, for each mobility class index $k^m = 1, \ldots, K^m$, and for each individual i in the sample (for that country), compute the posterior probability that i belongs to mobility class k^m given $\mathbf{x}_i$ and Θ_n^m:

$$\Pr\{k_i^m = k^m \mid \mathbf{x}_i; \Theta_n^m\} = \frac{\mathcal{L}_i^m(\mathbf{x}_i, k_i^m; \Theta_n^m)}{\sum_{k=1}^{K^m} \mathcal{L}_i^m(\mathbf{x}_i, k_i^m; \Theta_n^m)} \tag{F2}$$

M-step: Update Θ_n^m to Θ_{n+1}^m by maximizing the following augmented sample log-likelihood, weighted by F2:

$$\Theta_{n+1}^m = \arg\max_{\Theta^m} \sum_{i=1}^{N} \sum_{k=1}^{K^m} \Pr\{k_i^m = k \mid \mathbf{x}_i; \Theta_n^m\} \cdot \log\left[\mathcal{L}_i^m(\mathbf{x}_i, k_i; \Theta^m)\right] \tag{F3}$$

This maximization can be straightforwardly executed by running separate weighted logit regressions for ψ and χ (the parameters relating to the employment sector equations, (E4) and (E5)) and a separate weighted multinomial logit for the class weight parameters κ_k^m, using (F2) as the weights in each case. In theory this algorithm converges to the maximum-likelihood estimator of Θ^m (see Dempster *et al.*, 1977); in practice, we stop iterating when the maximum relative change in any of the parameters in Θ^m from one iteration to the next falls below 10^{-3} (i.e. less than a 0.1% change in any parameter between successive iterations). At this point we have our estimate of $\hat{\Theta}^m$.

F.1.2 Estimation of the Earnings Parameters Θ^y

The next stage is to estimate the second subset of parameters, those which relate to earnings, Θ^y. The natural approach at this stage would be to maximize the sample likelihood, $\mathcal{L}_i\left(\mathbf{x}_i, k_i; \hat{\Theta}^m, \Theta^y\right)$, with Θ^m fixed at its estimated value from the first stage of the estimation procedure, $\hat{\Theta}^m$. However, given the highly non-linear nature of $\mathcal{L}_i^y(\cdot)$ — see subsection 5.4 — even this maximisation is numerically impractical. Thus at this point we use a sequential, limited information, version of the EM algorithm. The procedure is as follows:

E-Step: For an arbitrary initial value Θ_n^y of Θ^y, for each class index $k = (k^m, k^y)$, with $k^m = 1, \ldots, K^m$, $k^y = 1, \ldots, K^y$, and for each individual i in the sample (for that country), compute the posterior probability that i belongs to mobility class k^m and wage class k^y given $\mathbf{x}_i$, Θ_n^y and $\hat{\Theta}^m$:

$$\Pr\left\{k_i^m = k^m, k_i^y = k^y \mid \mathbf{x}_i; \hat{\Theta}^m, \Theta_n^y\right\} = \frac{\mathcal{L}_i(\mathbf{x}_i, k^m, k^y; \hat{\Theta}^m, \Theta_n^y)}{\sum_{k^m=1}^{K^m} \sum_{k^y=1}^{K^y} \mathcal{L}_i(\mathbf{x}_i, k^m, k^y; \hat{\Theta}^m, \Theta_n^y)} \tag{F4}$$

M-step: This is the point at which our algorithm differs slightly from the standard EM algorithm. We proceed as follows:

1. Update income mean parameters $\mu(\cdot)$ using a weighted OLS regression of y_{it} on $\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, z_i^f, k_i^y\right)$, using (F4) as weights. Denote the updated function $\mu(\cdot)$ as $\widehat{\mu}_{n+1}(\cdot)$.

2. Take the log of the squared residuals from the latter regression and perform a weighted OLS regression of those on $\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, z_i^f, k_i^y\right)$, again using (F4) as the weights, to update the variance parameters $\sigma(\cdot)$. Denote the updated function as $\widehat{\sigma}_{n+1}(\cdot)$.

3. Form the log earnings disturbances $\tilde{y}_{it}^{(n+1)} = \frac{y_{it}-\widehat{\mu}_{n+1}\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, z_i^f, k_i^y\right)}{\widehat{\sigma}_{n+1}\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, z_i^f, k_i^y\right)}$. Update $\tau_1(\cdot)$ as:

$$\widehat{\tau}_{1,n+1}\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z_{it}^{v}, z_i^f, k_i^y\right) = \text{cov}\left(\tilde{y}_{it}^{(n+1)}, \tilde{y}_{i,t-1}^{(n+1)}\right), \tag{F5}$$

given that $\left(\tilde{y}_{it}^{(n+1)}, \tilde{y}_{i,t-1}^{(n+1)}\right)$ is distributed bivariate normal with unit variances. We do this by weighted maximum likelihood, again using (F4) as weights. Then we similarly update $\tilde{\tau}_2(\cdot)$ knowing that $\tau_2(\cdot) = \left(\tilde{y}_{it}^{(n+1)}, \tilde{y}_{i,t-2}^{(n+1)}\right)$ is given by the formula (E9), and that $\left(\tilde{y}_{it}^{(n+1)}, \tilde{y}_{i,t-2}^{(n+1)}\right)$ is again distributed bivariate normal with unit variances. Note that $\tau_1(\cdot)$ is involved in (E9) and that we replace it by $\widehat{\tau}_{1,n+1}$ for an update of $\tilde{\tau}_2(\cdot)$.

4. The final part is to update the set of earnings class assignment parameters, $(\kappa_k^y)_{k=1}^{K^y}$ by running a weighted multinomial logit regression of class indexes on $\left(z_i^f, k_i^m\right)$, again using (F4) as the weights.

We iterate between these E- and M-steps until the maximum relative change in any of the parameters in Θ^y from one iteration to the next falls below 10^{-3} (i.e. less than a 0.1% change in any parameter between successive iterations).

G Parameter Estimates

The EM algorithm procedures used to estimate the parameters of the model (described above in Appendix F) were run 100 times for each country in order to generate bootstrapped standard errors. In all models below is it these bootstrapped standard errors that are reported for the majority of coefficients. The exceptions are the wage and mobility class indicators and the constant. This is because the class number assigned to a specific type is arbitrary within the estimation. For example, the higher public earnings type is not necessarily given the same class number in each bootstrap sample – in some this will be labelled $k^y = 1$, in others $k^y = 2$ (though the people of this type will be the same people in each case, only the class number will be different). Consequently the standard deviation of the 100 coefficient estimates for the coefficient on the $k^y = 1$ dummy will not be the correct bootstrapped standard error, likewise for the $k^y = 2$ dummy (and similarly for the k^m dummies). For these indicator coefficients (and the constant) we therefore report the standard errors from the estimated model, which are approximate given the two-stage nature of the estimation.

G.1 Germany

Initial unemployment probability: $\Pr\left\{e_{i1}=0 \mid z_i^f, k_i^m\right\}$			
Experience (years/10)	-1.941 (0.272)	Experience^2 (years^2/100)	0.420 (0.064)
High education	0.075 (0.488)	Medium education	-0.216 (0.395)
$k^m=2$	-2.411 (0.137)	$k^m=3$	-2.886 (0.224)
Constant	1.049 (0.219)		
Initial probability of public sector: $\Pr\left\{\text{pub}_{i1}=1 \mid e_{i1}=1, z_i^f, k_i^m\right\}$			
Experience (years/10)	0.477 (0.628)	Experience^2 (years^2/100)	0.008 (0.143)
High education	0.919 (1.008)	Medium education	0.127 (0.943)
$k^m=2$	-15.693 (141.615)	$k^m=3$	3.467 (0.195)
Constant	-3.066 (0.405)		

Table G-1: Germany: Parameters of job sector mobility (logit models), initial conditions

Unemployment prob.: $\Pr\left\{e_{it}=0 \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^m\right\}$, $t \geq 2$			
Experience (years/10)	-1.819 (0.216)	Experience^2 (years^2/100)	0.428 (0.043)
High Education	-0.473 (0.453)	Medium Education	-0.105 (0.417)
Public last period: $\text{pub}_{i,t-1}=1$	0.804 (0.383)	Public last period × Experience	-0.242 (0.198)
Unempl. last period: $e_{i,t-1}=0$	1.343 (0.147)	Unempl. last period × Experience	0.365 (0.070)
$k^m=2$	-2.522 (0.069)	$k^m=3$	-4.130 (0.192)
Constant	0.620 (0.142)		
Prob. of public sector: $\Pr\left\{\text{pub}_{it}=0 \mid e_{it}=1, e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^m\right\}$, $t \geq 2$			
Experience (years/10)	-0.263 (0.287)	Experience^2 (years^2/100)	0.055 (0.056)
High Education	0.500 (0.424)	Medium Education	0.362 (0.388)
Public last period: $\text{pub}_{i,t-1}=1$	4.433 (0.266)	Public last period × Experience	0.367 (0.122)
Unempl. last period: $e_{i,t-1}=0$	1.883 (0.305)	Unempl. last period × Experience	0.180 (0.157)
$k^m=2$	-1.571 (0.152)	$k^m=3$	1.404 (0.138)
Constant	-3.849 (0.294)		

Table G-2: Germany: Parameters of job sector mobility (logit models), subsequent years

Earnings means: $\mu\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, z_{i}^{f}, k_{i}^{y}\right)$			
High education	0.335 (0.039)	Medium education	0.002 (0.027)
Experience (years/10)	0.156 (0.063)	Experience^2 (years^2/100)	−0.028 (0.013)
Public: $\text{pub}_{it} = 1$	−0.148 (0.060)	Experience×Public	0.094 (0.045)
Experience^2×Public	−0.011 (0.011)	Unemployed$_{i,t-1}$	−0.226 (0.021)
$k^y = 2$	−0.033 (0.009)	$(k^y = 2)$ ×Experience	−0.081 (0.010)
$(k^y = 2)$ ×Experience^2	0.012 (0.002)	$(k^y = 2)$ ×Public	0.013 (0.006)
Constant	8.258 (0.008)		
Earnings standard deviations: $\sigma\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, k_{i}^{y}\right)$			
Experience (years/10)	0.041 (0.035)	Public: $\text{pub}_{it} = 1$	−0.213 (0.080)
$k^y = 2$	0.232 (0.034)	Unemployed$_{i,t-1}$	0.183 (0.112)
Constant	−3.838 (0.041)		

Table G-3: Germany: Parameters of cross-sectional earnings means and standard deviations

First-order earnings autocorrelation: $\tau_1\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z_{it}^{v}, z_{i}^{f}, k_{i}^{y}\right)$			
$(k^y = 1)$ ×(High Education)	−3.185 (0.096)	$(k^y = 1)$ ×(Medium Education)	−2.508 (0.091)
$(k^y = 1)$ ×Public	−0.071 (0.088)	$(k^y = 1)$ ×(Public last period)	−0.257 (0.088)
$(k^y = 1)$ ×(Experience (years/10))	−0.391 (0.017)	$k^y = 1$	−0.428 (0.100)
$(k^y = 2)$ ×(High Education)	1.165 (0.057)	$(k^y = 2)$ ×(Medium Education)	1.539 (0.053)
$(k^y = 2)$ ×Public	0.172 (0.083)	$(k^y = 2)$ ×(Public last period)	−0.214 (0.083)
$(k^y = 2)$ ×(Experience (years/10))	−0.328 (0.016)	$k^y = 2$	−2.900 (0.061)
Second-order earnings autocorrelation: $\widetilde{\tau}_2\left(k_{i}^{y}\right)$			
$k^y = 1$	−0.604 (0.030)	$k^y = 2$	−0.608 (0.029)

Table G-4: Germany: Parameters of earnings mobility

Mobility heterogeneity: $\Pr\left\{k_i^m = 2 \mid z_i^f\right\}$			
Experience (years/10)	0.093 (0.043)	High Education	0.959 (0.157)
Medium education	0.362 (0.130)	Constant	0.610 (0.142)
Mobility heterogeneity: $\Pr\left\{k_i^m = 3 \mid z_i^f\right\}$			
Experience (years/10)	0.074 (0.053)	High Education	2.573 (0.266)
Medium education	1.745 (0.250)	Constant	−1.803 (0.260)
Earnings heterogeneity: $\Pr\left\{k_i^y = 2 \mid k_i^m, z_i^f\right\}$			
Experience (years/10)	0.118 (0.0368)	High Education	−0.287 (0.145)
Medium education	−0.887 (0.135)	$k^m = 2$	−3.201 (0.199)
$k^m = 3$	−3.612 (0.210)	Constant	3.548 (0.237)

Table G-5: Germany: Parameters of unobserved heterogeneity (multinomial logit models)

G.2 Netherlands

Initial unemployment probability: $\Pr\left\{e_{i1} = 0 \mid z_i^f, k_i^m\right\}$			
Experience (years/10)	−2.491 (0.343)	Experience^2 (years^2/100)	0.540 (0.103)
High education	−1.483 (0.421)	Medium education	−0.841 (0.244)
$k^m = 2$	−2.213 (0.208)	Constant	0.908 (0.252)
Initial probability of public sector: $\Pr\left\{\text{pub}_{i1} = 1 \mid e_{i1} = 1, z_i^f, k_i^m\right\}$			
Experience (years/10)	1.534 (1.535)	Experience^2 (years^2/100)	−0.208 (0.596)
High education	−0.449 (3.744)	Medium education	−0.417 (3.379)
$k^m = 2$	−20.835 (597.209)	Constant	0.420 (0.431)

Table G-6: Netherlands: Parameters of job sector mobility (logit models), initial conditions

Unemployment prob.: $\Pr\left\{e_{it} = 0 \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^m\right\}$, $t \geq 2$			
Experience (years/10)	−1.142 (0.259)	Experience^2 (years^2/100)	0.322 (0.059)
High Education	−0.801 (0.224)	Medium Education	−0.519 (0.142)
Public last period: $\text{pub}_{i,t-1} = 1$	−1.351 (1.373)	Unempl. last period: $e_{i,t-1} = 0$	3.888 (0.412)
$k^m = 2$	−1.435 (0.124)	Constant	−1.696 (0.214)
Prob. of public sector: $\Pr\left\{\text{pub}_{it} = 0 \mid e_{it} = 1, e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^m\right\}$, $t \geq 2$			
Experience (years/10)	0.699 (0.452)	Experience^2 (years^2/100)	−0.107 (0.082)
High Education	0.218 (0.353)	Medium Education	−0.058 (0.260)
Public last period: $\text{pub}_{i,t-1} = 1$	3.730 (0.249)	Unempl. last period: $e_{i,t-1} = 0$	0.874 (0.610)
$k^m = 2$	−3.782 (0.140)	Constant	−2.212 (0.240)

Table G-7: Netherlands: Parameters of job sector mobility (logit models), subsequent years

Earnings means: $\mu\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right)$			
High education	0.451 (0.018)	Medium education	0.110 (0.014)
Experience (years/10)	0.361 (0.044)	Experience^2 (years^2/100)	-0.061 (0.009)
Public: $\text{pub}_{it} = 1$	-0.137 (0.086)	Experience$\times$Public	-0.031 (0.052)
Experience^2$\times$Public	0.012 (0.012)	Unemployed$_{i,t-1}$	-0.134 (0.022)
$k^y = 2$	0.052 (0.009)	$(k^y = 2)$ $\times$Experience	-0.069 (0.009)
$(k^y = 2)$ $\times$Experience^2	0.010 (0.002)	$(k^y = 2)$ $\times$Public	0.187 (0.005)
Constant	8.138 (0.007)		
Earnings standard deviations: $\sigma\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^v, k_i^y\right)$			
Experience (years/10)	0.046 (0.045)	Public: $\text{pub}_{it} = 1$	-0.438 (0.151)
$k^y = 2$	-0.142 (0.038)	Unemployed$_{i,t-1}$	-0.035 (0.211)
Constant	-3.954 (0.050)		

Table G-8: Netherlands: Parameters of cross-sectional earnings means and standard deviations

First-order earnings autocorrelation: $\tau_1\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right)$			
$(k^y = 1)$ $\times$(High Education)	0.229 (0.055)	$(k^y = 1)$ $\times$(Medium Education)	2.138 (0.056)
$(k^y = 1)$ $\times$Public	-0.140 (0.092)	$(k^y = 1)$ $\times$(Public last period)	0.056 (0.092)
$(k^y = 1)$ $\times$(Experience (years/10))	-0.306 (0.022)	$k^y = 1$	-3.630 (0.059)
$(k^y = 2)$ $\times$(High Education)	-0.174 (0.074)	$(k^y = 2)$ $\times$(Medium Education)	-1.844 (0.061)
$(k^y = 2)$ $\times$Public	0.026 (0.084)	$(k^y = 2)$ $\times$(Public last period)	-0.104 (0.084)
$(k^y = 2)$ $\times$(Experience (years/10))	-0.311 (0.018)	$k^y = 2$	-1.479 (0.069)
Second-order earnings autocorrelation: $\widetilde{\tau}_2\left(k_i^y\right)$			
$k^y = 1$	-0.479 (0.037)	$k^y = 2$	-0.562 (0.030)

Table G-9: Netherlands: Parameters of earnings mobility

Mobility heterogeneity: $\Pr\left\{k_i^m = 2 \mid z_i^f\right\}$			
Experience (years/10)	-0.153 (0.045)	High Education	-1.267 (0.134)
Medium education	-0.190 (0.125)	Constant	1.619 (0.134)
Earnings heterogeneity: $\Pr\left\{k_i^y = 2 \mid k_i^m, z_i^f\right\}$			
Experience (years/10)	-0.030 (0.041)	High Education	0.046 (0.122)
Medium education	1.290 (0.107)	$k^m = 2$	-0.083 (0.095)
Constant	-0.316 (0.138)		

Table G-10: Netherlands: Parameters of unobserved heterogeneity (multinomial logit models)

G.3 France

Initial unemployment probability: $\Pr\left\{e_{i1}=0 \mid z_i^f, k_i^m\right\}$			
Experience (years/10)	-1.424 (0.546)	Experience^2 (years^2/100)	0.504 (0.115)
$k^m=2$	4.675 (0.302)	Constant	-4.489 (0.319)
Initial probability of public sector: $\Pr\left\{\text{pub}_{i1}=1 \mid e_{i1}=1, z_i^f, k_i^m\right\}$			
Experience (years/10)	0.409 (0.217)	Experience^2 (years^2/100)	-0.109 (0.051)
$k^m=2$	-0.759 (0.150)	Constant	-1.064 (0.166)

Table G-11: France: Parameters of job sector mobility (logit models), initial conditions

Unemployment prob.: $\Pr\left\{e_{it}=0 \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^m\right\},\ t\geq 2$			
Experience (years/10)	-0.684 (0.455)	Experience^2 (years^2/100)	0.346 (0.074)
Public last period: $\text{pub}_{i,t-1}=1$	-0.300 (0.426)	Unempl. last period: $e_{i,t-1}=0$	2.462 (0.181)
$k^m=2$	3.455 (0.140)	Constant	-5.290 (0.171)
Prob. of public sector: $\Pr\left\{\text{pub}_{it}=0 \mid e_{it}=1, e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^m\right\},\ t\geq 2$			
Experience (years/10)	-0.455 (0.307)	Experience^2 (years^2/100)	0.081 (0.079)
Public last period: $\text{pub}_{i,t-1}=1$	10.148 (0.315)	Unempl. last period: $e_{i,t-1}=0$	3.754 (0.765)
$k^m=2$	0.261 (0.273)	Constant	-5.013 (0.324)

Table G-12: France: Parameters of job sector mobility (logit models), subsequent years

Earnings means: $\mu\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right)$			
High education	0.653 (0.023)	Medium education	0.169 (0.016)
Experience (years/10)	0.459 (0.081)	Experience^2 (years^2/100)	-0.083 (0.019)
Public: $\text{pub}_{it}=1$	-0.043 (0.061)	Experience$\times$Public	0.001 (0.049)
Experience$^2\times$Public	0.006 (0.011)	Unemployed$_{i,t-1}$	-0.206 (0.019)
$k^y=2$	-0.010 (0.012)	$(k^y=2)\times$Experience	-0.104 (0.013)
$(k^y=2)\times$Experience^2	0.031 (0.003)	$(k^y=2)\times$Public	0.080 (0.007)
Constant	8.688 (0.011)		
Earnings standard deviations: $\sigma\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^v, k_i^y\right)$			
Experience (years/10)	0.098 (0.045)	Public: $\text{pub}_{it}=1$	-0.118 (0.089)
$k^y=2$	-0.527 (0.040)	Unemployed$_{i,t-1}$	-0.187 (0.147)
Constant	-3.391 (0.052)		

Table G-13: France: Parameters of cross-sectional earnings means and standard deviations

First-order earnings autocorrelation: $\tau_1\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^y\right)$			
$(k^y = 1)\times$(High Education)	-0.539 (0.076)	$(k^y = 1)\times$(Medium Education)	-0.150 (0.075)
$(k^y = 1)\times$Public	-0.093 (0.258)	$(k^y = 1)\times$(Public last period)	-0.073 (0.258)
$(k^y = 1)\times$(Experience (years/10))	-0.376 (0.026)	$k^y = 1$	-1.146 (0.092)
$(k^y = 2)\times$(High Education)	-0.666 (0.052)	$(k^y = 2)\times$(Medium Education)	-0.276 (0.041)
$(k^y = 2)\times$Public	0.071 (0.214)	$(k^y = 2)\times$(Public last period)	-0.285 (0.214)
$(k^y = 2)\times$(Experience (years/10))	-0.372 (0.019)	$k^y = 2$	-2.483 (0.058)
Second-order earnings autocorrelation: $\widetilde{\tau}_2\left(k_i^y\right)$			
$k^y = 1$	-0.666 (0.042)	$k^y = 2$	-0.653 (0.028)

Table G-14: France: Parameters of earnings mobility

Mobility heterogeneity: $\Pr\left\{k_i^m = 2 \mid z_i^f\right\}$			
Experience (years/10)	-1.420 (0.065)	High Education	-1.479 (0.148)
Medium education	-1.153 (0.128)	Constant	1.995 (0.148)
Earnings heterogeneity: $\Pr\left\{k_i^y = 2 \mid k_i^m, z_i^f\right\}$			
Experience (years/10)	-0.442 (0.052)	High Education	-1.483 (0.128)
Medium education	-0.363 (0.110)	$k^m = 2$	-2.048 (0.119)
Constant	2.378 (0.164)		

Table G-15: France: Parameters of unobserved heterogeneity (multinomial logit models)

G.4 Italy

Initial unemployment probability: $\Pr\left\{e_{i1} = 0 \mid z_i^f, k_i^m\right\}$			
Experience (years/10)	-5.495 (0.417)	Experience^2 (years^2/100)	1.089 (0.091)
High education	-0.624 (0.626)	Medium education	-0.567 (0.555)
$k^m = 2$	-5.245 (0.199)	$k^m = 3$	-2.568 (0.158)
Constant	6.580 (0.267)		
Initial probability of public sector: $\Pr\left\{\text{pub}_{i1} = 1 \mid e_{i1} = 1, z_i^f, k_i^m\right\}$			
Experience (years/10)	1.379 (1.148)	Experience^2 (years^2/100)	-0.239 (0.227)
High education	1.809 (2.575)	Medium education	0.913 (1.433)
$k^m = 2$	0.103 (0.200)	$k^m = 3$	-1.106 (0.222)
Constant	-3.239 (0.278)		

Table G-16: Italy: Parameters of job sector mobility (logit models), initial conditions

Unemployment prob.: $\Pr\left\{e_{it}=0 \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^{v}, z_i^{f}, k_i^{m}\right\}, t \geq 2$			
Experience (years/10)	-4.407 (0.507)	Experience^2 (years^2/100)	0.836 (0.086)
High Education	-0.983 (0.643)	Medium Education	-0.823 (0.514)
Public last period: $\text{pub}_{i,t-1}=1$	0.535 (0.889)	Public last period $\times$ Experience	-0.449 (0.231)
Unempl. last period: $e_{i,t-1}=0$	2.701 (0.216)	Unempl. last period $\times$ Experience	-0.123 (0.122)
$k^m=2$	-5.379 (0.128)	$k^m=3$	-2.240 (0.083)
Constant	4.751 (0.208)		
Prob. of public sector: $\Pr\left\{\text{pub}_{it}=0 \mid e_{it}=1, e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^{v}, z_i^{f}, k_i^{m}\right\}, t \geq 2$			
Experience (years/10)	0.065 (0.389)	Experience^2 (years^2/100)	-0.044 (0.077)
High Education	0.837 (0.390)	Medium Education	0.429 (0.209)
Public last period: $\text{pub}_{i,t-1}=1$	5.848 (0.516)	Public last period $\times$ Experience	0.464 (0.122)
Unempl. last period: $e_{i,t-1}=0$	2.275 (0.424)	Unempl. last period $\times$ Experience	0.084 (0.183)
$k^m=2$	-0.286 (0.188)	$k^m=3$	-0.654 (0.185)
Constant	-3.977 (0.301)		

Table G-17: Italy: Parameters of job sector mobility (logit models), subsequent years

Earnings means: $\mu\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, z_i^{f}, k_i^{y}\right)$			
High education	0.507 (0.028)	Medium education	0.150 (0.010)
Experience (years/10)	0.310 (0.049)	Experience^2 (years^2/100)	-0.055 (0.011)
Public: $\text{pub}_{it}=1$	0.206 (0.047)	Experience$\times$Public	-0.151 (0.038)
Experience$^2\times$Public	0.025 (0.008)	$\text{Unemployed}_{i,t-1}$	-0.126 (0.010)
$k^y=2$	-0.004 (0.009)	$(k^y=2)\times$Experience	-0.052 (0.009)
$(k^y=2)\times$Experience^2	0.016 (0.002)	$(k^y=2)\times$Public	-0.017 (0.004)
Constant	7.484 (0.008)		
Earnings standard deviations: $\sigma\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, k_i^{y}\right)$			
Experience (years/10)	-0.080 (0.047)	Public: $\text{pub}_{it}=1$	0.014 (0.067)
$k^y=2$	-0.603 (0.037)	$\text{Unemployed}_{i,t-1}$	0.238 (0.114)
Constant	-3.665 (0.052)		

Table G-18: Italy: Parameters of cross-sectional earnings means and standard deviations

First-order earnings autocorrelation: $\tau_1\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z^v_{it}, z^f_i, k^y_i\right)$			
$(k^y=1)\times$(High Education)	-0.171 (0.069)	$(k^y=1)\times$(Medium Education)	-0.195 (0.052)
$(k^y=1)\times$Public	-0.210 (0.108)	$(k^y=1)\times$(Public last period)	-0.110 (0.109)
$(k^y=1)\times$(Experience (years/10))	-0.227 (0.024)	$k^y=1$	-1.100 (0.081)
$(k^y=2)\times$(High Education)	-1.015 (0.080)	$(k^y=2)\times$(Medium Education)	-0.311 (0.039)
$(k^y=2)\times$Public	0.450 (0.099)	$(k^y=2)\times$(Public last period)	-0.677 (0.099)
$(k^y=2)\times$(Experience (years/10))	-0.474 (0.020)	$k^y=2$	-1.593 (0.052)
Second-order earnings autocorrelation: $\widetilde{\tau}_2\left(k^y_i\right)$			
$k^y=1$	-0.533 (0.034)	$k^y=2$	-0.544 (0.030)

Table G-19: Italy: Parameters of earnings mobility

Mobility heterogeneity: $\Pr\left\{k^m_i=2 \mid z^f_i\right\}$			
Experience (years/10)	0.302 (0.050)	High Education	0.802 (0.185)
Medium education	0.268 (0.108)	Constant	1.040 (0.120)
Mobility heterogeneity: $\Pr\left\{k^m_i=3 \mid z^f_i\right\}$			
Experience (years/10)	0.062 (0.054)	High Education	-0.398 (0.215)
Medium education	0.107 (0.115)	Constant	0.875 (0.127)
Earnings heterogeneity: $\Pr\left\{k^y_i=2 \mid k^m_i, z^f_i\right\}$			
Experience (years/10)	-0.712 (0.034)	High Education	-1.937 (0.123)
Medium education	-0.564 (0.072)	$k^m=2$	1.560 (0.113)
$k^m=3$	0.591 (0.118)	Constant	0.680 (0.123)

Table G-20: Italy: Parameters of unobserved heterogeneity (multinomial logit models)

G.5 Spain

Initial unemployment probability: $\Pr\left\{e_{i1}=0 \mid z_i^f, k_i^m\right\}$			
Experience (years/10)	-3.347 (0.245)	Experience^2 (years^2/100)	0.633 (0.061)
High education	-0.385 (0.324)	Medium education	-0.114 (0.268)
$k^m=2$	0.424 (0.195)	$k^m=3$	3.829 (0.212)
Constant	0.167 (0.232)		
Initial probability of public sector: $\Pr\left\{\text{pub}_{i1}=1 \mid e_{i1}=1, z_i^f, k_i^m\right\}$			
Experience (years/10)	3.654 (3.768)	Experience^2 (years^2/100)	-0.723 (2.093)
High education	-0.109 (3.993)	Medium education	-0.524 (3.385)
$k^m=2$	-22.637 (377.577)	$k^m=3$	-7.136 (0.497)
Constant	0.257 (0.527)		

Table G-21: Spain: Parameters of job sector mobility (logit models), initial conditions

Unemployment prob.: $\Pr\left\{e_{it}=0 \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^m\right\}$, $t \geq 2$			
Experience (years/10)	-2.991 (0.225)	Experience^2 (years^2/100)	0.569 (0.049)
High Education	-0.482 (0.219)	Medium Education	-0.187 (0.210)
Public last period: $\text{pub}_{i,t-1}=1$	-0.422 (0.479)	Public last period $\times$ Experience	0.112 (0.130)
Unempl. last period: $e_{i,t-1}=0$	1.469 (0.148)	Unempl. last period $\times$ Experience	0.199 (0.065)
$k^m=2$	-0.018 (0.129)	$k^m=3$	2.647 (0.127)
Constant	-0.269 (0.167)		
Prob. of public sector: $\Pr\left\{\text{pub}_{it}=0 \mid e_{it}=1, e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^v, z_i^f, k_i^m\right\}$, $t \geq 2$			
Experience (years/10)	0.140 (0.620)	Experience^2 (years^2/100)	-0.022 (0.106)
High Education	0.353 (0.290)	Medium Education	0.072 (0.254)
Public last period: $\text{pub}_{i,t-1}=1$	3.906 (0.407)	Public last period $\times$ Experience	0.085 (0.157)
Unempl. last period: $e_{i,t-1}=0$	1.183 (0.389)	Unempl. last period $\times$ Experience	0.057 (0.159)
$k^m=2$	-3.772 (0.136)	$k^m=3$	-1.954 (0.126)
Constant	-1.626 (0.256)		

Table G-22: Spain: Parameters of job sector mobility (logit models), subsequent years

Earnings means: $\mu\left(\text{pub}_{it}, e_{i,t-1}, z^v_{it}, z^f_i, k^y_i\right)$			
High education	0.500 (0.049)	Medium education	0.199 (0.037)
Experience (years/10)	0.418 (0.108)	Experience^2 (years^2/100)	−0.061 (0.020)
Public: $\text{pub}_{it} = 1$	0.185 (0.086)	Experience×Public	−0.075 (0.061)
Experience^2×Public	0.011 (0.012)	Unemployed$_{i,t-1}$	−0.210 (0.014)
$k^y = 2$	0.182 (0.013)	$(k^y = 2)$ ×Experience	−0.145 (0.013)
$(k^y = 2)$ ×Experience^2	0.026 (0.003)	$(k^y = 2)$ ×Public	0.015 (0.008)
Constant	11.500 (0.011)		

Earnings standard deviations: $\sigma\left(\text{pub}_{it}, e_{i,t-1}, z^v_{it}, k^y_i\right)$			
Experience (years/10)	0.057 (0.046)	Public: $\text{pub}_{it} = 1$	−0.312 (0.202)
$k^y = 2$	−0.858 (0.037)	Unemployed$_{i,t-1}$	−0.314 (0.109)
Constant	−3.035 (0.047)		

Table G-23: Spain: Parameters of cross-sectional earnings means and standard deviations

First-order earnings autocorrelation: $\tau_1\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z^v_{it}, z^f_i, k^y_i\right)$			
$(k^y = 1)$ ×(High Education)	−1.336 (0.068)	$(k^y = 1)$ ×(Medium Education)	−0.618 (0.077)
$(k^y = 1)$ ×Public	−0.193 (0.087)	$(k^y = 1)$ ×(Public last period)	−0.022 (0.086)
$(k^y = 1)$ ×(Experience (years/10))	−0.245 (0.021)	$k^y = 1$	−1.033 (0.083)
$(k^y = 2)$ ×(High Education)	1.266 (0.074)	$(k^y = 2)$ ×(Medium Education)	−0.527 (0.050)
$(k^y = 2)$ ×Public	0.157 (0.115)	$(k^y = 2)$ ×(Public last period)	−0.272 (0.113)
$(k^y = 2)$ ×(Experience (years/10))	−0.317 (0.021)	$k^y = 2$	−1.373 (0.058)

Second-order earnings autocorrelation: $\widetilde{\tau}_2\left(k^y_i\right)$			
$k^y = 1$	−0.668 (0.034)	$k^y = 2$	−0.629 (0.033)

Table G-24: Spain: Parameters of earnings mobility

Mobility heterogeneity: $\Pr\left\{k_i^m = 2 \mid z_i^f\right\}$			
Experience (years/10)	-0.243 (0.048)	High Education	-2.050 (0.134)
Medium education	-1.159 (0.147)	Constant	2.949 (0.155)

Mobility heterogeneity: $\Pr\left\{k_i^m = 3 \mid z_i^f\right\}$			
Experience (years/10)	-0.267 (0.054)	High Education	-2.033 (0.148)
Medium education	-1.289 (0.163)	Constant	2.097 (0.168)

Earnings heterogeneity: $\Pr\left\{k_i^y = 2 \mid k_i^m, z_i^f\right\}$			
Experience (years/10)	-0.084 (0.041)	High Education	-3.494 (0.124)
Medium education	-1.376 (0.101)	$k^m = 2$	-0.013 (0.124)
$k^m = 3$	-1.748 (0.148)	Constant	1.779 (0.165)

Table G-25: Spain: Parameters of unobserved heterogeneity (multinomial logit models)

G.6 UK

Initial unemployment probability: $\Pr\left\{e_{i1} = 0 \mid z_i^f, k_i^m\right\}$			
Experience (years/10)	-2.152 (0.503)	Experience^2 (years^2/100)	0.453 (0.115)
High education	-0.853 (1.476)	Medium education	-2.304 (1.703)
$k^m = 2$	-3.457 (0.185)	$k^m = 3$	-3.687 (0.282)
Constant	2.639 (0.306)		

Initial probability of public sector: $\Pr\left\{\text{pub}_{i1} = 1 \mid e_{i1} = 1, z_i^f, k_i^m\right\}$			
Experience (years/10)	2.445 (0.619)	Experience^2 (years^2/100)	-0.517 (0.162)
High education	1.384 (1.956)	Medium education	0.787 (2.648)
$k^m = 2$	-3.164 (0.590)	$k^m = 3$	4.344 (0.348)
Constant	-6.253 (0.574)		

Table G-26: UK: Parameters of job sector mobility (logit models), initial conditions

Unemployment prob.: $\Pr\left\{e_{it}=0 \mid e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^{v}, z_{i}^{f}, k_{i}^{m}\right\}$, $t \geq 2$			
Experience (years/10)	-1.269 (0.245)	Experience^2 (years^2/100)	0.247 (0.045)
High Education	-0.430 (0.353)	Medium Education	-1.439 (0.513)
Public last period: $\text{pub}_{i,t-1}=1$	-0.392 (0.455)	Public last period $\times$ Experience	-0.017 (0.173)
Unempl. last period: $e_{i,t-1}=0$	1.892 (0.291)	Unempl. last period $\times$ Experience	0.195 (0.117)
$k^m=2$	-2.414 (0.095)	$k^m=3$	-1.908 (0.148)
Constant	0.113 (0.198)		

Prob. of public sector: $\Pr\left\{\text{pub}_{it}=0 \mid e_{it}=1, e_{i,t-1}, \text{pub}_{i,t-1}, z_{it}^{v}, z_{i}^{f}, k_{i}^{m}\right\}$, $t \geq 2$			
Experience (years/10)	1.235 (0.499)	Experience^2 (years^2/100)	-0.247 (0.090)
High Education	0.733 (0.576)	Medium Education	0.429 (0.753)
Public last period: $\text{pub}_{i,t-1}=1$	4.130 (0.417)	Public last period $\times$ Experience	0.282 (0.215)
Unempl. last period: $e_{i,t-1}=0$	2.191 (0.507)	Unempl. last period $\times$ Experience	-0.098 (0.214)
$k^m=2$	-1.959 (0.263)	$k^m=3$	2.598 (0.178)
Constant	-6.198 (0.392)		

Table G-27: UK: Parameters of job sector mobility (logit models), subsequent years

Earnings means: $\mu\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, z_{i}^{f}, k_{i}^{y}\right)$			
High education	0.278 (0.022)	Medium education	0.073 (0.038)
Experience (years/10)	0.388 (0.069)	Experience^2 (years^2/100)	-0.073 (0.015)
Public: $\text{pub}_{it}=1$	0.013 (0.090)	Experience$\times$Public	0.057 (0.067)
Experience$^2\times$Public	-0.016 (0.015)	Unemployed$_{i,t-1}$	-0.182 (0.020)
$k^y=2$	-0.021 (0.016)	$(k^y=2)$ $\times$Experience	0.115 (0.016)
$(k^y=2)$ $\times$Experience^2	-0.024 (0.004)	$(k^y=2)$ $\times$Public	-0.027 (0.010)
Constant	6.804 (0.012)		

Earnings standard deviations: $\sigma\left(\text{pub}_{it}, e_{i,t-1}, z_{it}^{v}, k_{i}^{y}\right)$			
Experience (years/10)	-0.013 (0.034)	Public: $\text{pub}_{it}=1$	-0.221 (0.101)
$k^y=2$	0.166 (0.040)	Unemployed$_{i,t-1}$	-0.021 (0.123)
Constant	-3.192 (0.049)		

Table G-28: UK: Parameters of cross-sectional earnings means and standard deviations

First-order earnings autocorrelation: $\tau_1\left(\text{pub}_{it}, \text{pub}_{i,t-1}, z^v_{it}, z^f_i, k^y_i\right)$			
$(k^y = 1)\,\times$(High Education)	1.410 (0.048)	$(k^y = 1)\,\times$(Medium Education)	1.599 (0.096)
$(k^y = 1)\,\times$Public	0.215 (0.104)	$(k^y = 1)\,\times$(Public last period)	−0.615 (0.103)
$(k^y = 1)\,\times$(Experience (years/10))	−0.265 (0.021)	$k^y = 1$	−2.777 (0.065)
$(k^y = 2)\,\times$(High Education)	−2.813 (0.073)	$(k^y = 2)\,\times$(Medium Education)	−2.641 (0.104)
$(k^y = 2)\,\times$Public	−0.622 (0.105)	$(k^y = 2)\,\times$(Public last period)	0.149 (0.104)
$(k^y = 2)\,\times$(Experience (years/10))	−0.384 (0.023)	$k^y = 2$	−0.576 (0.092)
Second-order earnings autocorrelation: $\widetilde{\tau}_2\,(k^y_i)$			
$k^y = 1$	−0.580 (0.034)	$k^y = 2$	−0.364 (0.039)

Table G-29: UK: Parameters of earnings mobility

Mobility heterogeneity: $\Pr\left\{k^m_i = 2 \mid z^f_i\right\}$			
Experience (years/10)	0.009 (0.057)	High Education	0.095 (0.147)
Medium education	−1.159 (0.204)	Constant	1.510 (0.171)
Mobility heterogeneity: $\Pr\left\{k^m_i = 3 \mid z^f_i\right\}$			
Experience (years/10)	−0.064 (0.069)	High Education	0.244 (0.177)
Medium education	−1.309 (0.293)	Constant	0.325 (0.206)
Earnings heterogeneity: $\Pr\left\{k^y_i = 2 \mid k^m_i, z^f_i\right\}$			
Experience (years/10)	−0.112 (0.043)	High Education	0.610 (0.110)
Medium education	0.952 (0.201)	$k^m = 2$	2.684 (0.212)
$k^m = 3$	2.612 (0.226)	Constant	−2.968 (0.241)

Table G-30: UK: Parameters of unobserved heterogeneity (multinomial logit models)

H Lifetime Values Robustness Tests

H.1 Robustness to value of the retirement income replacement rate

	Whole Sample			Whole sample, with selection		
Germany	**10th**	**50th**	**90th**	**10th**	**50th**	**90th**
Public & Private RR=0.40	4.95	0.57	-2.22	8.11	5.23	3.52
Private RR=0.70, Public RR=0.75	6.76	1.67	-1.02	10.15	6.87	5.35
Netherlands						
Public & Private RR=0.40	3.54	-1.31	-5.09	7.97	6.18	3.43
Private RR=0.70, Public RR=0.70	3.93	-1.21	-4.26	8.58	7.28	4.12
France						
Public & Private RR=0.40	9.05	5.69	3.10	13.47	12.92	11.22
Private RR=0.71, Public RR=0.75	10.19	7.17	3.90	13.92	14.44	11.98
Italy						
Public & Private RR=0.40	-1.87	0.25	2.29	0.48	4.21	15.30
Private RR=0.70, Public RR=0.80	1.26	2.09	3.60	4.17	7.45	17.92
Spain						
Public & Private RR=0.40	8.45	7.17	4.73	21.74	26.52	21.04
Private RR=0.88, Public RR=0.95	11.24	8.24	5.15	20.82	26.98	21.61
UK						
Public & Private RR=0.40	0.53	1.06	0.52	8.35	3.84	2.52
Private RR=0.70, Public RR=0.70	0.50	0.36	-0.51	8.85	3.01	1.77

Notes: For each country the upper number is taken from Table 27 and is the percentile of the LTV distribution when a common public and private retirement income replacement rate of 0.4 times final salary is used. The lower figure shows the corresponding value when the indicated alternative RRs are used.

Table H-1: Public premia (log points) in Lifetime Values, with different retirement income replacement rates, selected percentiles of the distribution

	Whole sample			Whole sample, with selection		
Germany	**Private**	**Public**	**Diff.**	**Private**	**Public**	**Diff.**
Public & Private RR=0.40	11.25	11.26	0.01	11.25	11.30	0.05
Private RR=0.70, Public RR=0.75	11.32	11.34	0.02	11.31	11.38	0.07
Netherlands						
Public & Private RR=0.40	11.52	11.51	-0.01	11.50	11.56	0.06
Private RR=0.70, Public RR=0.70	11.58	11.57	-0.01	11.57	11.63	0.06
France						
Public & Private RR=0.40	12.21	12.27	0.06	12.19	12.31	0.13
Private RR=0.71, Public RR=0.75	12.28	12.35	0.07	12.25	12.39	0.14
Italy						
Public & Private RR=0.40	10.75	10.75	0.00	10.71	10.77	0.06
Private RR=0.70, Public RR=0.80	10.81	10.83	0.02	10.78	10.87	0.09
Spain						
Public & Private RR=0.40	15.14	15.21	0.07	15.10	15.34	0.24
Private RR=0.88, Public RR=0.95	15.25	15.34	0.08	15.22	15.46	0.24
UK						
Public & Private RR=0.40	10.25	10.26	0.01	10.25	10.29	0.04
Private RR=0.70, Public RR=0.70	10.31	10.31	0.00	10.30	10.34	0.04

Notes: For each country the upper number is taken from Table 28 and is the mean LTV when a common public and private retirement income replacement rate of 0.4 times final salary is used. The lower figure shows the corresponding mean value when the indicated alternative RRs are used.

Table H-2: Public premia in (log) Lifetime Values with different retirement income replacement rates

H.2 Alternative counterfactual exercise

As discussed in section 7.1, we run a series of counterfactual simulations in which we constrain the probability of moving between sectors or into unemployment to be zero (i.e. assigning individuals to a 'job for life' in each sector) and simulate their earnings trajectories. An alternative exercise places individuals in a sector initially and then simulates earnings *and* mobility trajectories over the lifetime using the parameters from our estimated model. The lifetime value for the individual when they *begin* in the private (public) sector is then their private (public) sector lifetime value and the two distributions can be compared. We do not observe earnings when an individual is unemployed therefore for the purposes of constructing a lifetime value – allowing for movement into and out of unemployment, and at different rates according to the sector – we need to make some assumptions regarding replacement rates for unemployment earnings. We use figures from the OECD on gross replacement rates, which themselves are averaged over a number of different demographic/family structure categories. These rates are: Germany 25%, Netherlands 50%, France 40%, Italy 25%, Spain 35%, UK 20%.

The limitation of this exercise is that individuals with a strong tendency to work in the private sector, if initially placed in the public sector and allowed to lose his job will find subsequent employment in the private sector with a very high probability and pursue his subsequent career within that sector. As a consequence, any observed public premium will only be derived from years spent in that sector prior to a first unemployment episode. This is illustrated in the figures below which depict the public premium in earnings and lifetime values for the whole sample when we constrain movement (left side) and do not (right side). For most countries, the public premium when we allow movement is close to zero across the whole of the distribution – this indicates that even if an individual is started in their less natural sector, they quickly transit to their more natural sector and stay there, hence their lifetime trajectories are very similar regardless of their initial sector. This leads to very similar public and private lifetime values distributions and hence little public premium. The exception to this is France. There the very low job loss rate in the public sector means that individuals who start in the public sector remain there for a long time, hence the 'job for life' simulation and the simulation allowing movement are actually very similar and this is reflected in the lifetime values public premium.

Figure H.1: **Germany**: Public Premia in Lifetime Values, with and without mobility

Figure H.2: **Netherlands**: Public Premia in Lifetime Values, with and without mobility

Figure H.3: **France**: Public Premia in Lifetime Values, with and without mobility

Figure H.4: **Italy**: Public Premia in Lifetime Values, with and without mobility

Figure H.5: **Spain**: Public Premia in Lifetime Values, with and without mobility

Figure H.6: **UK**: Public Premia in Lifetime Values, with and without mobility