Earnings and Labor Market Dynamics: Indirect Inference Based on Swedish Register Data

Johan Holmberg*

January 2021

Abstract

In this paper, we present a life-cycle earnings dynamics model including endogenous employment and job change. The model is estimated with the method of indirect inference using Swedish register data. By simulating data from this microeconomic model, we study the macroeconomic consequences of transitory shocks to unemployment risk. The results show that transitory aggregate shocks to unemployment risk have long-lasting negative effects on employment, income, and increases earnings volatility. By studying how unemployment at different ages affects the accumulation and distribution of pension entitlements, we find that becoming unemployed at 40 has the largest effect on pension accumulations. Furthermore, unobserved individual heterogeneity contributes substantially to the observed life-cycle earnings inequality for both men and women in Sweden.

Keywords: Earnings dynamics, unemployment, inequality, social insurance, pensions

1 Introduction

The primary objective of this paper is to increase our understanding of the factors determining the earnings and employment of individuals over their working lives. To this end, we build and estimate a multivariate model of individual labor market outcomes including

*Umeå University, e-mail: johan.holmberg@umu.se. First, I wish to express my gratitude to Gauthier Lanot, Thomas Aronsson, Katharina Jenderny, Giovanni Forchini, and Johan Lundberg for their valuable input during the writing process as well as seminar participants at Umeå University, 76th Annual Congress of the IIPF, the 2019 PSE summer school and the Scandinavian PhD Seminar series for their questions and comments. Financial support provided by the Jan Wallander and Tom Hedelius and Tore Browaldhs Foundation grant P2017-0217:1 *Human Capital, Heterogeneity and the Performance of Social Insurance*, is gratefully acknowledged.

life-cycle earnings, job changes, and transitions in and out of employment. The model includes multiple dimensions of unobserved heterogeneity to capture the effects of differences in unobserved characteristics across individuals. It also includes state dependence which allows for individual-level inter-dependency between the different labor market processes. The aggregate response to any given shock depends on how the individuals constituting these aggregates react to the shock. If one considers an aggregate shock to unemployment, then the pool of unemployed is over time increasingly represented by individuals that are more prone to stay in unemployment, even within groups with the same observable characteristics (Ahn and Hamilton, 2020).[1] Even when individual heterogeneity is constant over time, it still affects the current state of the system making the responses in terms of aggregated statistics sensitive to the timing of a shock. Many important aspects of the labor market could be conflated in an analysis of the aggregates alone, if individual differences, state- and inter-dependencies are ignored. For example, if transition probabilities vary across the earnings distribution, then this will affect the distributional effects of macroeconomic shocks.

The estimated model will be used to address three key aspects of labor market dynamics and life-cycle earnings. First, we predict the effects that transitory macro shocks to the unemployment probability have on the dynamic behavior of average incomes, employment levels, job changes, and earnings risk by simulating individual-level data. Recognizing the potential costs of macroeconomic shocks is important when formulating policies aimed at alleviating their impact, in particular when determining the appropriate magnitude of the response. Second, we provide an analysis of how the accumulation and distribution of pension entitlements for men and women respond to unemployment spells occurring at different ages. This is an important margin to consider when evaluating the individual cost of a job loss at different stages of the working life. Finally, we attempt to measure the relative importance of the underlying factors contributing to life-cycle earnings inequality. A better understanding of life-cycle labor dynamics provides useful information for both fiscal policy considerations and for designing and evaluating social insurance systems.

[1]Other examples are how heterogeneous marginal propensities to consume affect the extent to which income- and wealth shocks translate into changes in expenditure. Heterogeneity is important for understanding how income shocks (e.g., Alan et al., 2018) and wealth destruction (e.g., Kaplan and Violante, 2018) affect the aggregate demand.

The approach implemented in this paper builds on that of Altonji et al. (2013). They constructed a semi-structural[2] earnings dynamics[3] model with endogenous job mobility and employment, and estimated this model on PSID data using indirect inference. Their modeling framework is similar to that of Low et al. (2010), who analyzed wage dynamics by combining an earning dynamics model with a model of endogenous job mobility and employment based on a search-theoretic framework.[4] These studies went beyond the traditional earnings dynamics literature by modeling some of the underlying sources behind the observed earnings inequality.[5] For example, Low et al. (2010) found that the size of permanent shocks becomes smaller when allowing for endogenous transitions, and that wage shocks are to a large extent a result of individuals changing jobs to firms offering better matches. Altonji et al. (2013) used their model to decompose the sources of earnings risk and variance in lifetime earnings to provide an estimate of the importance of the firm match, unemployment shocks, and job changes for life-cycle earnings inequality. They found that job-specific heterogeneity in wages contributes to 34 % of the variance in life-cycle earnings. Other contributions to this literature can be found in Sauer and Taber (2017) who provided a model of life-cycle wages with endogenous human capital accumulation, and fertility and applied it to female workers using U.S. data.[6] The present paper contributes to this literature by using this modeling framework to analyze key labor market dynamics and by analyzing Swedish labor market data.

Friedrich et al. (2019) estimate an earnings dynamics model with endogenous labor mar-

[2]A semi-structural model can be thought of as a model that identifies some of the mechanisms and parameters of a structural model without including fully specified behavioral components.

[3]There is a large literature on earnings dynamics based on the permanent income hypothesis of Friedman and Kuznets (1954) and Friedman (1957) where earnings inequality is decomposed into permanent differences and transitory shocks. Important contributions to this literature include Lillard and Willis (1978), Lillard and Weiss (1979), Hause (1980), MaCurdy (1982), Moffitt and Gottschalk (1995), and Guvenen (2007). Gustavsson (2008), Gustavsson and Österholm (2014), and Gustafsson and Holmberg (2019) provide some recent examples of earnings dynamics literature using Swedish data.

[4]See among others Mortensen (1977), Pissarides (1985), Mortensen and Pissarides (1994) and Burdett and Mortensen (1998). Lise et al. (2016), Jung and Kuhn (2019) and Merkurieva (2019) provides examples of recent applications of structural search theoretical models.

[5]Traditional earnings dynamics models only provide descriptive information such as the extent to which the observed inequality is a result of systematic differences or temporary shocks.

[6]They found that female wages would be 3 % higher if there were no relationship between fertility and labor market participation

ket transitions using Swedish data. They study how firm-level productivity shocks affect earnings dynamics when participation is endogenous and find that firm heterogeneity contributes substantially to the wage inequality of college-educated workers. Compared with Friedrich et al. (2019), the model developed in this paper has a more comprehensive specification of the labor market transitions with a stronger focus on their non-wage determinants. More specifically, the model in this paper also account for education, state dependence, migration, and fertility. Furthermore, we give a more prominent role in unobserved individual heterogeneity and analyze both male and female labor market data.[7]

The analysis is conducted using Swedish register data from the ASTRID database, which includes geographical and socioeconomic information for the Swedish population born 1936—1997 over the period 2002–2015. The estimations are carried out using indirect inference (Smith, 1990, 1993; Gourieroux et al., 1993). The main findings are as follows. First, temporary aggregate shocks to unemployment risk have negative effects that linger on the labor market 10 years after the shock affecting aggregate earnings levels, earnings risk, and the unemployment probability. The long recovery time and high costs in terms of foregone earnings provide arguments for devoting significant resources to mitigate these shocks. Secondly, unemployment early in the working life has a smaller negative effect on life-cycle earnings and pension accumulations than shocks occurring in the middle ages. Thirdly, the pension entitlements of workers with low education are more sensitive to unemployment shocks and would benefit more than the college-educated workers from the inclusion of unemployment insurance in pension contributions. We also find an elasticity in potential earnings of an additional year of schooling of 3.1 % and 4.6 % for male and female workers. This is in line with previous studies on the returns to education using Swedish data[8] and is consistent with the compressed wage structure in Sweden.[9] Finally, we find that a large fraction of the observed life-cycle earnings inequality can be attributed to unobserved individual heterogeneity.

This paper will continue as follows: The economic model will be introduced in the next

[7]To the best of my knowledge, Sauer and Taber (2017) provides the only other example of female labor market data being analyzed using this type of modeling framework.

[8]For example Isacsson (1999) or Björklund (2000).

[9]The Swedish wage structure is one of the most compressed in the European Union and has remained stable since 2001 (Gottfries, 2018).

section. Section 3 discusses the estimation procedure and the data will be presented and discussed in section 4. Results and an evaluation of the fit of the model are presented in section 5. Section 6 provides three applications of the model while section 7 provides some concluding remarks.

2 Model

The economic model will be presented in this section. This model specifies the data generating process that is used in the simulations. The specification is based on the framework of Altonji et al. (2013), but with some differences. While Altonji et al. (2013) model wages, hours, and earnings, my analysis focuses on earnings. We put more emphasis on the role of exogenous determinants in my analysis and have modified the model to be more appropriate for analyzing the labor market outcomes of both males and females.

Earnings and labor market transitions depend on different sets of variables, both exogenous variables, and variables generated within the model. The set of observable variables include years of education, potential experience,[10] workplace tenure, employment and unemployment duration. It also includes dummy variables indicating whether the worker migrated to another municipality, spent time away from the labor market due to parental leave, or due to short spells of unemployment during the year. The unobserved variables include individual heterogeneity such as individual ability (α) and propensity to change employer (η) as well as an unobserved job match process. All equations share a set of common regressors including years of education, a polynomial of order two in potential experience, and unobserved ability. Only the additional variables will be mentioned in the following sections.

2.1 Earnings

A presentation of the model of earnings can be found in this section. The model focuses on residual log earnings, where economy-wide effects have been removed by subtracting the

[10]Measured as age minus years of education normalized to take values between -1 and 1 using Chebyshev polynomials.

yearly means from log earnings among the employed.[11] The residual earnings process was specified as follows:

$$earn_{it} = E_{it} earn_{it}^{lat}, \tag{1}$$

$$earn_{it}^{lat} = X_{it}^{earn} \theta_{earn}^{earn} + \theta_{\alpha}^{earn} \alpha_i + \theta_m^{earn} m_{ift} + \omega_{it}, \tag{2}$$

$$m_{ift} = (1 - S_{it}) m_{if,t-1} + S_{it} m_{if't}, \tag{3}$$

$$m_{if't} = \rho_m m_{if,t-1} + \epsilon_{it}^m, \tag{4}$$

$$\omega_{it} = \rho_\omega \omega_{i,t-1} + \epsilon_{it}^{earn}, \tag{5}$$

$$\omega_{i0} = \epsilon_{i0}^{earn}. \tag{6}$$

The observed residual earnings ($earn_{it}$) is the realization of latent earnings ($earn_{it}^{lat}$) through employment (E_{it}), which assumes the value 1 when the individual is employed. Index i is used to refer to individuals while index t refers to the year. The first part of the latent earnings (X_{it}^{earn}) refers to a set of observable variables including current workplace tenure, current employment duration, and a set of dummies indicating whether the worker has received unemployment benefits or has been on parental leave at some point during the current or previous year. These variables are treated as exogenous to the model but would be possible to internalize within this framework.[12] The second component ($\theta_{\alpha}^{earn} \alpha_i$) captures the direct effect of unobserved ability on earnings. Unobserved individual ability is assumed to be constant over time and drawn from a standard normal distribution. The coefficient θ_{α}^{earn} is without loss of generality normalized to be non-negative.[13]

In the third part, (m_{ift}) is the value of a job match where the index f refers to the workplace. The parameter θ_m^{earn} scales the value of a match to yearly log earnings. Equations (3) and (4) describe the job match process. In the case that a worker switches job in a given year

[11] This as the latent earnings of the unemployed cannot be observed.

[12] For example, Friedrich et al. (2019) analyze unemployment at a quarterly level. However, we do not have the necessary data to do this. It is also possible to include endogenous migration decisions based on local labor market conditions (see for example Nenov (2015)), extend the model to include endogenous fertility decisions (see Choi, 2017; Saez et al., 2017) or allowing for unobserved geographic heterogeneity or neighborhood effects (for example discussed in Lindbeck et al. (2016)).

[13] This restriction facilitates interpretation of the estimates across the multiple processes in which the variable α_i is included.

the variable S_{it} assumes the value 1, otherwise it is 0. The job match can change as a result of two different events, either as a result of currently employed individuals deciding to change employer or from previously unemployed individuals finding new employment. Previously employed individuals that remain in employment have two options, they can either stay with their current employer and keep the job match from the previous period ($m_{if,t-1}$) or switch employer and obtain an alternative match ($m_{if't}$). Workers that return from unemployment can only obtain the alternative job match. Due to the data being observed at a yearly frequency one can consider $m_{if't}$ as the best available offer. Equation (4) describes the process of generating alternative job offers. The alternative job match offers are allowed to be partially based on the previous period's job match, with ρ_m estimating the correlation between offers. This specification differs from the standard search models[14] but allows for network effects where the worker's position could be connected to his or her network[15] or the possibility of firms tailoring their offers for the candidate they consider, taking their current wages into account.[16] The job match shock (ϵ_{it}^{m}) is drawn from a standard normal distribution. Current job matches are assumed to be unaffected by alternative job offers, the employee cannot use an outside offer to negotiate a better match with the current employer. Friedrich et al. (2019) allows for updates of worker-firm match effects, but find that this effect is small.

The final component (ω_{it}) consists of a transitory shock process modeled as an AR(1), with normally distributed i.i.d errors with an unknown standard deviation (ϵ_{it}^{earn}) and a shock upon initial labor market entry (ϵ_{i0}^{earn}) drawn from an independent normal distribution.

2.2 Transitions and states

In this section, the transition equations which determine employment and job change will be presented. Employment (E_{it}) is determined by two processes in this model; the probability of remaining in employment for the employed and the probability for the unemployed to find new employment. These two processes will be referred to as employment to employment- (E_{it}^{E}) and unemployment to employment (U_{it}^{E}) transitions. They assume the value 1 in the

[14] In which the offers are commonly considered to be independent draws from a distribution (see for example Mortensen (1977) or Burdett and Mortensen (1998))

[15] See for example Marmaros and Sacerdote (2002) or Loury (2006).

[16] See for example Bagger et al. (2014).

case that the transition results in employment and 0 otherwise.

The probability of remaining in employment depends on many factors. First, a set of observable characteristics (X_{it}^{EE}) which, in addition to the common regressors, include workplace tenure ($D_{i,t-1}^{T}$) and employment duration ($D_{i,t-1}^{E}$) at the beginning of the period. It also contains dummy variables indicating whether the worker migrated, was temporarily unemployed, or on parental leave at any point during the year. The third factor (η_i) measures the unobserved propensity to change employer. This heterogeneity is assumed to be constant over time and standard normally distributed in the population. The term ϵ_{it}^{EE} is an i.i.d error drawn from a standard normal distribution.

$$E_{it}^{E} = I\Big[X_{it}^{EE}\theta_X^{EE} + \theta_\alpha^{EE}\alpha_i + \theta_\eta^{EE}\eta_i + \epsilon_{it}^{EE} > 0\Big],\ if\ E_{i,t-1} = 1. \tag{7}$$

The probability of leaving unemployment depends on the observable characteristics (X_{it}^{UE}) including the unemployment duration ($D_{i,t-1}^{U}$) at the beginning of the period and dummy variables indicating whether the individual migrated, spent any time on parental leave or received any unemployment benefits. It also depends on unobserved heterogeneity such as the unobserved ability and propensity to change employer. Similarly to Equation (7) then ϵ_{it}^{UE} is an i.i.d error term assumed to be drawn from a standard normal distribution.

$$U_{it}^{E} = I\Big[X_{it}^{UE}\theta_X^{UE} + \theta_\alpha^{UE}\alpha_i + \theta_\eta^{UE}\eta_i + \epsilon_{it}^{UE} > 0\Big],\ if\ E_{i,t-1} = 0. \tag{8}$$

Equations (7) and (8) determine employment status. An employed individual must either have remained in employment from the preceding period or transitioned back into employment from a previous unemployment spell. If $E_{it} = 0$, then the individual is unemployed.

$$E_{it} = E_{it}^{E}E_{i,t-1} + U_{it}^{E}(1 - E_{i,t-1}). \tag{9}$$

The employment status determines both employment and unemployment duration which in turn affects the transition probabilities and earnings. This model therefore captures state dependence like a renewal process.[17] Each year the individual remains in a state, the duration increases and they reset whenever a worker changes state.

[17] See Karlin and Taylor (1975) chapter 5 for example.

$$D_{it}^E = E_{it}(1 + D_{i,t-1}^E), \tag{10}$$

$$D_{it}^U = (1 - E_{it})(1 + D_{i,t-1}^U). \tag{11}$$

An individual who has remained in employment[18] gets to decide whether to change employer and keep the job match ($m_{if,t-1}$) from the previous period or switch job and receive an alternative job match ($m_{if',t}$). This decision is captured by Equation (12). The probability for a job change depends on a set of observable and unobserved variables as well as on a random error (ϵ_{it}^{JC}) drawn from an i.i.d standard normal distribution. The set of observable variables (X_{it}^{JC}) includes a polynomial of order three in potential experience, tenure and employment duration at the beginning of the year, and dummies indicating whether the individual migrated, received unemployment benefits or was on parental leave. The set of unobserved variables include individual unobserved ability (α_i) and the unobserved preference to change job (η_i). The parameter θ_η^{JC} is normalized to be non-negative in this equation. The value of the current job match ($m_{if,t-1}$) and the alternative job offer ($m_{if't}$) are allowed to affect the probability of a job change.[19] The variable JC_{it} assumes the value 1 if the worker changes job and 0 otherwise and the job change process is modeled to have the following form:

$$\begin{gathered} JC_{it} = I\Big[X_{it}^{JC}\theta_X^{JC} + \theta_{m,t-1}^{JC} m_{if,t-1} + \theta_{ma}^{JC} m_{if't} + \theta_\alpha^{JC}\alpha_i + \theta_\eta^{JC}\eta_i + \epsilon_{it}^{JC} > 0\Big], \\ if\ E_{it} = E_{i,t-1} = 1. \end{gathered} \tag{12}$$

The job change and employment transitions together determine the tenure. Tenure measures firm-specific experience and is defined as the number of years in a row an individual has had the same workplace. This is determined in the following fashion:

$$D_{it}^T = E_{i,t-1}E_{it}^E\big((1 - JC_{it})(D_{i,t-1}^T + 1) + JC_{it}\big) + (1 - E_{i,t-1})U_{it}^E \tag{13}$$

Tenure is allowed to affect the probability of remaining in employment and the probability

[18] Made a successful E_{it}^E transition.

[19] Friedrich et al. (2019) specify their job change process using the difference in match value. Similar to Altonji et al. (2013), we choose to estimate the effects for the match values separately as this allows for asymmetric effects from the current and alternative job match. This could for example be the case if individuals have a status quo bias.

of changing employer as well as earnings which give another dimension of state dependence within the model.

3 Estimation

The estimation method used in the analysis will be described in this section. Methods such as maximum likelihood or the general method of moments were not feasible due to the complexity of the model. Instead, we used a procedure based on indirect inference. Smith (1990) was first to propose the indirect inference framework which is a generalization of simulation-based inference methods, such as the simulated method of moments[20] (Gourieroux et al., 1993). This method is built on the specification of an intermediary statistic (or auxiliary models) and simulations from the model of interest. The intermediate statistics do not have to identify the parameters of interest directly, instead, they summarize key features of the data. The estimation is done by finding the parameter values that minimize the difference between the simulated and observed data.

In general, auxiliary models are miss-specified, which in a likelihood context means that the true conditional density of the true model is not accurately described by the density of the auxiliary model (Smith, 1993).[21] This means that it is possible to substitute the likelihood function generated by the model of interest with a likelihood that can be solved analytically, given that it captures the same properties of the data. You then estimate the parameters of the data generating process indirectly using the alternative likelihood as an intermediate step. The use of indirect inference facilitates the estimation of models that would be difficult or even impossible to estimate using direct methods.

We use a likelihood-based objective similar to the simulated quasi-maximum likelihood objective suggested by Smith (1993).[22] An advantage of this approach, compared to distance-

[20]See McFadden (1989) for further description of this method.

[21]In a distance-based context, this miss-specification can be interpreted as the auxiliary model not directly providing a consistent estimator for the parameters of the economic model (Gourieroux et al., 1993).

[22]Other approaches include matching simulated data with the observed auxiliary parameter estimates and evaluating the distance between the auxiliary parameter estimates from the real data with their simulated counterparts (Fackler and Tastan, 2008). In the case of exact identification (when $p = k$) these three approaches yield the same estimator while in the case of over-identification they

based alternatives, is that there is no need to define and estimate a weighting matrix to scale the differences between the observed and simulated moment conditions. A more general description of indirect inference can be found in Appendix A. Unlike both Low et al. (2010) and Altonji et al. (2013), all parameters of the model in this paper were estimated using indirect inference. The estimations were done using the numerical optimization package BB (Varadhan and Gilbert, 2009) in R with a local search. Up to 40 quasi-Newton steps were taken before implementing the local search, this procedure was then repeated 20 times.

3.1 Auxiliary model

The auxiliary model will be described in this section. This model provides a descriptive measurement of the similarity between the observed and simulated data and is used to define the objective function. The auxiliary model shares many similarities with the economic model as it is designed to capture the dimensions of the data necessary for identifying the structural parameters.

As the objective of the model is to explain a large set of interrelationships between several labor market outcomes, we specify a model with a large set of parameters that broadly captures the statistical properties of the data and data generating process. A rich auxiliary model is more likely to capture these relationships than a model focusing on a few key variables. The auxiliary model used in this analysis consists of three components and is built around the framework used by Altonji et al. (2013). As suggested in Bruins et al. (2018), the auxiliary model was constructed using linear probability models which are both efficient and easy to compute. The first component provides information on the variables determining residual earnings and has the following linear form:

$$\begin{aligned} E_{it} earn_{it}^{aux} &= \beta_0 + \beta_1 edu_i + P(xp_{it})\beta_{xp}^{e,aux} + \beta_5 D_{it}^T \\ &+\beta_6 D_{it}^E + \beta_7 u_{it} + \beta_8 u_{i,t-1} + \beta_9 pl_{it} + \beta_{10} pl_{i,t-1} + \varepsilon_{it} \end{aligned} \tag{14}$$

In this equation realized residual log earnings is a function of years of education (edu_i), a polynomial of order two in potential experience (xp_{it}), current tenure (D_{it}^T) and employment

are asymptotically equivalent.

duration (D^E_{it}), dummies for temporary unemployment the current or previous year (u_{it} and $u_{i,t-1}$), and dummies for parental leave (pl_{it} and $pl_{i,t-1}$). These are the observable variables of the latent earnings equation. The final term (ε_{it}) is an i.i.d error following a normal distribution. This first part of the auxiliary model has 10 auxiliary parameters. Following Altonji et al. (2013) the predictions from this model are used to calculate a residual $e\tilde{arn}_{it}$ which is used in the estimation of other parts of the auxiliary model. As X^{earn}_{it} contains lagged variables, we cannot calculate the auxiliary model for the first year of observation.

The second and third part of the auxiliary model consist of a set of seemingly unrelated regression (SUR) models. Both contains five equations and have common sets of regressors. These systems can be written as:

$$Y_{it} = B^s X^s_{it} + e_{it},\ e_{it},\ iid \sim N(0, \Omega) \tag{15}$$

Y_{it} represents the following vector of dependent variables:

$$Y_{it} = [E^E_{it},\ U^E_{it},\ JC_{it},\ e\tilde{arn}_{it},\ ln(1 + e\tilde{arn}^2_{it})] \tag{16}$$

For the second part of the auxiliary model, X^s_{it} represents the following sets of common regressors:

$$\begin{gathered} X^{s2}_{it} = \Big[1,\ xp_{it},\ xp^2_{it},\ xp^3_{it}, edu_i, \\ D^T_{i,t-1},\ mig_{it},\ u_{it},\ u_{i,t-1},\ pl_{it},\ pl_{i,t-1},\ D^E_{i,t-1},\ D^U_{i,t-1} \\ E^E_{i,t-1}, E^E_{i,t-2},\ U^E_{i,t-1},\ U^E_{i,t-2},\ JC_{i,t-1},\ JC_{i,t-2}, \\ earn_{i,t-1},\ earn_{i,t-2},\ earn_{i,t-3},\ earn_{i,t-1}xp_{i,t}, earn_{i,t-1}xp^2_{i,t}, \\ earn_{i,t-1}JC_{it},\ earn_{i,t-2}JC_{i,t-1},\ earn_{i,t-3}JC_{i,t-2}, earn_{i,t-2}E_{i,t-1}\Big], \\ if\ age > 28\ and\ calendar\ year > 2005 \end{gathered} \tag{17}$$

Naturally, the explanatory variables for the transition equations of the economic model were included in the auxiliary model to capture the correlation between these variables and the outcomes of interest. The fifth dependent variable $ln(1+e\tilde{arn}^2_{it})$ aims to capture information for the the variance terms of the model. This transformation of $e\tilde{arn}_{it}$ gives a measure of the distance between each observed residual and its predicted value while the logarithmic transformation reduces the spread of the data. The lagged earnings terms inform about the autoregressive components while the interaction between lagged earnings residuals and job changes aims to identify the correlations between mobility and earnings. The use of lagged variables in the set of regressors facilitates the separation of heterogeneity and state dependence at the cost of losing the first four years of individual observations. As 2002 is the first year observed in the data and since labor market entry is modeled to occur at the age of 25, the use of variables lagged up to three periods mean that only individuals age 29 or older observed after 2005 are included in this likelihood. A third likelihood was therefore added to provide information on the first years on the labor market, and for the initial period for the auxiliary model.

$$\begin{gathered} X_{it}^{s3} = \Big[1,\ xp_{it},\ xp_{it}^2,\ xp_{it}^3, edu_i, \\ D_{i,t-1}^T,\ mig_{it},\ u_{it},\ u_{i,t-1},\ pl_{it},\ pl_{i,t-1},\ D_{i,t-1}^E,\ D_{i,t-1}^U\Big], \\ if\ age < 29\ or\ calendar\ year < 2006 \end{gathered} \tag{18}$$

The assumption of independent and identically distributed errors e_{it} is violated for numerous reasons. The set of dependent variables include two versions of the same earnings where one is just a monotonic transformation of the other as well as three binary outcomes. This affects the efficiency of the indirect estimator, but not its consistency (Altonji et al., 2013). The first system of equations includes 140 parameters in its B^s and the second has 65. In addition, both of the covariance matrices have 15 unique elements each. The auxiliary model overall includes 245 parameters which exceeds the 49 parameters of the economic model. Unlike Altonji et al. (2013), we do not add any weights to the first part of the likelihood. Instead, the different likelihoods are scaled by their relative number of observations using the first auxiliary likelihood as reference.

3.1.1 Smoothing

Discrete events are a central part of the model and give rise to discontinuities in the objective. This is problematic when using gradient-based optimization. Keane and Smith (2003)[23] suggest to modify the simulation process so that it produces approximations to the discrete

[23] Further developed in Bruins et al. (2018).

indicators that are continuous in the parameters of the model. One then compares the output of this "smoothed" data generating process with that from the observed data. Although the estimation procedures for the observed and simulated data are not exactly the same, this approach produces consistent estimates if the auxiliary models converge to the same binding function as the number of observations asymptotically approaches infinity and the smoothing factor (λ) approaches 0 (Bruins et al., 2018). Following Keane and Smith (2003), we use the following smoothing procedure:

$$g(\tilde{u}_{it}^{m}(\theta);\lambda) = \frac{1}{1 + exp(-\tilde{u}_{it}^{m}(\theta)/\lambda)} \tag{19}$$

If $\lambda > 0$ then the output from $g(.)$ will be continuous function of the parameters of the economic model since the latent utilities are continuous in these dimensions. If $\lambda = 0$ then the transformation made by Equation (19) would produce the same binary output as an indicator function. The smooth output from these utilities were used to create a continuous measure of employment status, job changes and tenure. It is important to note that this smoothing procedure introduces an approximation error into the model. Increasing the number of repetitions (M) further increases the smoothness of the objective, but also increases the computational burden (Keane and Smith, 2003). It is therefore important to find a balance between the bias that the smoothing factor generates, the computation time and the necessary smoothness of the objective. Following Altonji et al. (2013), we use a smoothing parameter (λ) of 0.05. During the estimation, we simulate 100,000 individuals over 39 periods and repeat the simulation 10 times (M) for each function evaluation.

3.2 Starting values and standard errors

The starting values used in the estimation were taken from a set of independent probit regressions for the transition equations and a linear regression for the earnings process. The initial conditions for the modified AR(1) process were obtained by fitting this model component to the covariance structure of the earnings residual obtained from the linear regression using minimum distance estimation. These models were fitted to the data using only the observable variables. For the unobserved variables, then the parameters for θ_{α}^{earn}, θ_{η}^{JC}, θ_{m}^{earn} and $\theta_{m,t-1}^{JC}$ were initially set to 0.1. The parameters θ_{ma}^{JC} and ρ_m were set to -0.1 and 0.5

respectively. All starting values can be found in Appendix B. Standard errors have been calculated using a bootstrap procedure with 100 seed resamplings.

4 Data

We use Swedish register data from the ASTRID database. This data set includes socioeconomic and geographical data for the Swedish population born between 1936–1997 over the years 2002–2015 resulting in a panel with 7,478,807 individuals observed over a fourteen-year period. This data was collected and organized by Statistics Sweden (SCB) and hosted at the Department of Geography and Economic History at Umeå university (Stjernström, 2011). Register data has a number of advantages over survey data, which has been employed in previous studies such as Low et al. (2010), Altonji et al. (2013) and Alan et al. (2018). The information does not rely on the recollection of the subjects and there is no potentially systematic attrition from the data, apart from emigration or death.

The analysis focuses on prime-age employees defined as individuals age 25–59. Due to the use of lagged variables and the inclusion of auto-regressive variables, we required at least 10 years of possible observations. This meant that only individuals born 1952–1985 are considered. Any spell of self-employment or employment as a sailor is disregarded from the data. The measure of income in this analysis includes all compensations subject to labor income taxation. This includes travel reimbursements, shares of profit, holiday compensations, or other benefits such as company cars, etc. Earnings are measured in 100 SEK among the employed and the residuals are generated by removing the yearly means from the log of earnings calculated among the employed. Workplace identity (CFAR) was used to measure tenure in the analysis. The analysis was conducted using a subset of the data including 1,902,758 men with 21,313,846 individual/year observations and 1,863,825 women with 21,926,975 individual/year observations.

The individual time series in the observed data generally starts later than the year for labor market entry, which creates a problem with initial conditions.[24] If standard panel

[24]For further reading on the problem of initial conditions when estimating discrete models using panel data see Heckman (1981).

methods were to be used, then the truncation of the data in combination with the unobserved heterogeneity would result in inconsistent and biased parameter estimates. Indirect inference can be used to construct consistent estimators of labor market transitions when dealing with left-censored data and unobserved heterogeneity (An and Liu, 2000). This approach is robust from bias resulting from the initial conditions problem as the probability limits for both estimators of the auxiliary model[25] are affected the same way (Altonji et al., 2013).

4.1 Simulation of independent variables, sampling and initial conditions

The estimations are based on simulated data for 100,000 individuals with 10 repetitions. The simulated individuals are assigned a year of birth and an education level based on the observed frequencies for each combination.[26] Initial employment status during the individual's first year on the labor market is simulated based on the observed employment rates. For the cohorts born 1977–1981, the probability of being employed the first year on the labor market is based on the employment rates observed in the ASTRID data. The probability of being employed at the age of 25 for the cohorts born 1952–1976 are based on the average employment rates for individuals 25–34 over the years 1977–2001 collected from Statistics Sweden's Labor Force Surveys. Shocks such as a missing status,[27] migrating, receiving parental allowance, or becoming short-term unemployed are assigned based on observed probabilities. The probabilities used are conditioned on age and education.[28]

5 Results

The empirical findings are presented and discussed in this section. The first sub-section focuses on the estimates of the model. The second part discusses aspects of the model fit

[25] $\hat{\beta}$ and $\tilde{\beta}(\theta)$, see Section 3.1.

[26] For example, in the male sample then 0.17% were born 1952 and had 7 years of education. This meant that a simulated individual was assigned this year of birth and education combination with a 0.17% probability.

[27] Either due to missing earnings observation, being a sailor, being self-employed, or receiving pension payments.

[28] For example, a woman aged 30 with 15 years of education had a 19.8% probability of receiving parental allowance during that year.

to the data. Estimates of the parameters of the latent residual earnings[29] process are presented in Table 1 while Table 2 presents estimates for the parameters corresponding to the labor market transition equations. The estimated marginal effects of a set of variables on the final transition probability can be found in Appendix C. The fit of the model is evaluated by comparing descriptive linear regressions made on the observed and simulated data as well as through a comparison of aggregate statistics from the observed and simulated data.

5.1 Parameter estimates

From Table 1, we find that the marginal effect of an additional year of continuous employment on the expected latent earnings is greater than both the marginal effect of workplace tenure and an additional year of education. The estimated coefficient for employment duration is 0.054 (0.048) while the estimated elasticity of an additional year of education is 0.031 (0.046) for men (women). These estimates are consistent with the compressed wage structures of the Swedish labor market and are in line with previous studies on the returns to education in Sweden. Isacsson (1999) found a 4.5 % return to years of schooling in terms of earnings for the population at large while Björklund (2000) found 4 % hourly wage premium per additional year of education. Estimating the effects of a major educational reform Meghir and Palme (2005) found an upper bound for the returns to educations for the overall population of 8.4 %, as the reform affected both quantity and type of education. Similar to my analysis, they also found that the overall effect of the reform on earnings was larger for females than males. My elasticities for latent earnings are slightly lower. However, the present model also allows education to affect the realization of earnings by affecting the employment probability.

A spell of parental leave affects female earnings negatively and part of this effect persists in the following year. Men do not seem to be affected in the same way, their estimated coefficient for the direct effect is positive. This could be a result of paternal leave being more common among higher socioeconomic groups. For example, Bygren and Duvander (2006) found that education and higher income correlated with a higher probability of paternal

[29]Measured as the log of 100 SEK with demeaned by year and gender among the employed.

leave take up and that income also correlated positively with the duration of the paternal leave. A dedicated month of paternal leave was introduced in 1995 in Sweden. Analyzing the effect of this reform, Ekberg et al. (2013) found that it increased male parental leave but not the males' long-run share of child care. The negative effect of parental leave on female earnings and the unclear effect on male earnings found in this paper is in line with women bearing a larger share of the labor market cost of child-rearing.

The estimated coefficient of the AR(1) process for the transitory shock to earnings is far from a unit root in this model. For men, the estimated coefficient is 0.510 while it is 0.368 for women. This is in line with previous findings within the earnings dynamics literature. For example, Gustavsson and Österholm (2014) concluded that male earnings do not seem to be governed by a unit root process in Sweden. The estimated persistence of shocks found in this paper is slightly lower than their median estimates when individual trends are included. Gustavsson and Österholm (2014) differentiate by education groups in their analysis but the estimates are all between 0.603 and 0.652. Other examples are Gustavsson (2007) who found an AR(1) of 0.555 for men and Gustavsson (2008) who estimated an AR(1) of 0.572 for male earnings between 1968–1990. Estimates for females are less common, my estimates for the AR(1) is in line with those of Gustafsson and Holmberg (2019) who found estimates in the range 0.344–0.375 evaluating different education groups. Earnings shocks are less persistent for females but more variable, both upon initial entry into the labor market and when reaching the steady-state of the AR(1) process.

We find that the match quality has a low positive persistence between employers. The estimated correlation between the match heterogeneity is 0.137 (0.100) for men (women). Which is much lower than the match-quality persistence of 0.691 for male wages found by Altonji et al. (2013). However, their analysis was conducted using U.S. data and there are many important institutional differences between these labor markets such as the level of unionization and the fraction of employees that are covered by collective bargaining agreements. Friedrich et al. (2019) model estimated on Swedish data allows for within-firm dynamics of wages but does not include persistence of match quality between firms.

Turning to Table 2, we find that education has a positive effect on the probability of being employed. (Weber, 2002) found similar results for several European countries (including Sweden). The effect is larger on the job-finding rate than on the probability of remaining in employment. That education has a larger positive effect on the probability of re-entering employment than on unemployment risk is in line with the findings of Riddell and Song (2011) studying U.S. data.

We also find that the effect of match quality on the propensity to change employer is asymmetric. The relative value of an alternative offer has a larger effect on the probability for a job change than the value of the current job match.[30] This is consistent with the findings of Low et al. (2010) who found that individual mobility accounting for preferences of better-paying jobs can explain a substantial part of permanent productivity shocks.

Employment duration has a larger effect on the probability of remaining in employment than workplace tenure. This suggests that remaining in employment is more important for reducing the risk of future unemployment than remaining with a particular employer. However, tenure length matters more for the probability for a job change.

Among the many results, it is worth noting that unobserved earnings ability is positively associated with the probability of remaining in employment and negatively associated with the probability to find new employment. From a search theoretical point of view, this could be due to higher reservation wages among more productive individuals. We also find that women are less likely to become unemployed after receiving a short-term unemployment shock than men. Furthermore, migration has a positive effect on the probability of finding new employment when unemployed but correlates negatively with the probability of remaining in employment.

[30]Remember that the match heterogeneity shock is drawn from a standard normal distribution. This heterogeneity is later converted to annual log earnings using the parameter θ_m^{earn} in Equation 2.

	Male Earnings	Female Earnings
$Constant$	-1.465	-1.568
	(0.0000)	(0.0000)
$Education$	0.031	0.046
	(0.0000)	(0.0000)
xp	-0.736	-0.377
	(0.0000)	(0.0000)
xp^2	-0.214	-0.235
	(0.0000)	(0.0000)
D_{it}^T	0.004	0.010
	(0.0000)	(0.0000)
D_{it}^E	0.054	0.048
	(0.0000)	(0.0000)
u_{it}	-0.772	-0.467
	(0.0000)	(0.0000)
$u_{i,t-1}$	-0.210	-0.165
	(0.0000)	(0.0000)
pl_{it}	0.100	-0.211
	(0.0000)	(0.0000)
$pl_{i,t-1}$	-0.022	-0.051
	(0.0000)	(0.0000)
θ_{α}^{earn}	0.355	0.401
	(0.0000)	(0.0000)
ρ_m	0.137	0.100
	(0.0000)	(0.0000)
θ_m^{earn}	0.357	0.373
	(0.0000)	(0.0000)
ρ_{ω}	0.510	0.368
	(0.0000)	(0.0000)
σ^{earn}	0.375	0.574
	(0.0000)	(0.0000)
σ_0^{earn}	1.378	2.009
	(0.0000)	(0.0000)

Table 1: Parameter estimates for latent log earnings for male and female workers.
Note: Standard errors are presented in brackets beneath the estimates.

	Males			Females		
	E^E	U^E	JC	E^E	U^E	JC
Constant	1.280	-1.021	-0.817	1.017	-1.525	-0.926
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education	0.012	0.026	0.007	0.033	0.053	0.020
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xp	-0.503	-0.483	-0.378	0.103	-0.294	-0.330
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
xp^2	0.117	0.310	-0.005	-0.010	0.003	-0.004
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xp^3	-	-	-0.106	-	-	-0.048
			(0.0000)			(0.0000)
$D^T_{i,t-1}$	0.033	-	-0.055	0.032	-	-0.049
	(0.0000)		(0.0000)	(0.0000)		(0.0000)
$D^E_{i,t-1}$	0.074	-	-0.005	0.073	-	-0.002
	(0.0000)		(0.0000)	(0.0000)		(0.0000)
$D^U_{i,t-1}$	-	-0.078	-	-	-0.080	-
		(0.0000)			(0.0000)	
u_{it}	-1.034	-	1.076	-0.627	-	1.020
	(0.0000)		(0.0000)	(0.0000)		(0.0000)
pl_{it}	0.706	-	-0.108	0.032	-	-0.196
	(0.0000)		(0.0000)	(0.0000)		(0.0000)
mig_{it}	-0.200	0.353	0.486	-0.117	0.182	0.511
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\theta^{JC}_{m,t-1}$	-	-	-0.190	-	-	-0.199
			(0.0000)			(0.0000)
θ^{JC}_{ma}	-	-	0.357	-	-	0.410
			(0.0000)			(0.000)
θ_α	0.415	-0.287	0.022	0.415	-0.287	0.036
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_η	0.075	0.363	0.262	-0.017	-0.365	0.151
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table 2: Parameter estimates for transition equations for males and females.
Note: Standard errors are presented in brackets beneath the estimates.

5.2 Model fit

To assess the fit of the model, we use the estimated parameter values and a sample of 100,000 initial conditions and shocks[31] from the ASTRID data to simulate the working life for 100,000 males and females. First, we compare the relationship between labor market outcomes and the observable characteristics for the simulated and observed data using a set of descriptive linear regressions. Then, we compare the mean values over the life-cycle for some key variables from the simulated data with the corresponding values from the observed data. These values are presented as a 95% confidence interval, but due to the sample size, this spread is relatively narrow.

5.2.1 Comparing regressions on simulated and actual data

The results from a set of linear descriptive regressions for the key labor market outcomes are presented in Tables 3 and 4. Output for males is presented in Table 3 while Table 4 contains the results for females. These regressions provide descriptive statistics of the labor market outcomes analyzed by the model to enable a comparison of the data generated by the model and the real data. Most parameter estimates are of similar size and with a few exceptions have the same sign. The fit of the linear models is also similar between the observed and simulated data. Both adjusted R-square values and residual standard errors are of similar magnitudes. The difference in the size of standard errors can be attributed to the difference in sample size between the real and the simulated data.

[31] Individual data on migrations, type of employment, parental allowances, and unemployment benefits.

	$Earn \| E_{it} = 1$		$E^E_{it} \| E_{i,t-1} = 1$		$U^E_{it} \| E_{i,t-1} = 0$		$JC_{it} \| E^E_{it} = 1$	
	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
Constant	−1.143 (0.001)	−1.332 (0.005)	0.949 (0.0002)	0.917 (0.001)	0.153 (0.001)	0.195 (0.004)	0.216 (0.001)	0.241 (0.003)
Education	0.039 (0.0001)	0.025 (0.0003)	−0.001 (0.00002)	−0.003 (0.0001)	−0.001 (0.0001)	0.005 (0.0003)	0.001 (0.00004)	0.0004 (0.0002)
xp	−0.434 (0.001)	−0.820 (0.003)	−0.058 (0.0002)	−0.107 (0.001)	−0.130 (0.0005)	−0.096 (0.002)	−0.099 (0.001)	−0.106 (0.003)
xp^2	−0.151 (0.001)	−0.192 (0.002)	0.009 (0.0001)	0.014 (0.001)	0.055 (0.0005)	0.085 (0.002)	0.039 (0.0003)	0.025 (0.001)
xp^3							−0.021 (0.0003)	−0.025 (0.001)
D^T_{it}	0.003 (0.00003)	−0.007 (0.0001)						
D^E_{it}	0.046 (0.00004)	0.064 (0.0001)						
$D^T_{i,t-1}$			0.0004 (0.00001)	0.0004 (0.00003)			−0.009 (0.00002)	−0.010 (0.0001)
$D^E_{i,t-1}$			0.004 (0.00001)	0.008 (0.00003)			0.0001 (0.00002)	−0.0002 (0.0001)
u_{it}	−0.566 (0.001)	−0.752 (0.004)	−0.065 (0.0001)	−0.104 (0.001)			0.351 (0.0004)	0.332 (0.002)
$u_{i,t-1}$	−0.199 (0.001)	−0.206 (0.004)						
pl_{it}	0.038 (0.001)	0.101 (0.002)	0.016 (0.0001)	0.024 (0.0004)			−0.016 (0.0002)	−0.028 (0.001)
$pl_{i,t-1}$	−0.008 (0.001)	−0.022 (0.002)						
$D^U_{i,t-1}$					0.004 (0.00005)	−0.016 (0.0002)		
mig_{it}			−0.006 (0.0002)	−0.015 (0.001)	0.072 (0.001)	0.077 (0.003)	0.133 (0.0005)	0.137 (0.002)
Observations	14,267,098	909,279	14,679,221	909,139	4,159,430	179,512	15,833,262	886,874
Adj. R^2	0.228	0.315	0.047	0.113	0.023	0.062	0.099	0.094
Res. SE	0.661	0.672	0.128	0.144	0.287	0.293	0.350	0.353

Table 3: Linear regressions for key outcomes using observed (Obs) and simulated (Sim) data for male sample and model.

Note: Standard errors are presented in parenthesis beneath estimated coefficients. Conditions for selection are based on rounded predictions for the simulated data.

	$Earn\|E_{it}=1$		$E^E_{it}\|E_{i,t-1}=1$		$U^E_{it}\|E_{i,t-1}=0$		$JC_{it}\|E^E_{it}=1$	
	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
Constant	−1.135 (0.002)	−1.380 (0.006)	0.926 (0.0003)	0.896 (0.001)	0.165 (0.001)	0.127 (0.005)	0.181 (0.001)	0.200 (0.003)
Education	0.047 (0.0001)	0.037 (0.0004)	0.001 (0.00002)	−0.0003 (0.0001)	0.001 (0.0001)	0.009 (0.0003)	0.004 (0.00005)	0.004 (0.0002)
xp	−0.176 (0.001)	−0.508 (0.004)	−0.028 (0.0002)	−0.033 (0.001)	−0.188 (0.001)	−0.057 (0.002)	−0.096 (0.001)	−0.122 (0.003)
xp^2	−0.217 (0.001)	−0.187 (0.003)	0.002 (0.0001)	−0.004 (0.001)	0.051 (0.001)	0.034 (0.002)	0.034 (0.0003)	0.024 (0.001)
xp^3							−0.016 (0.0004)	−0.018 (0.001)
D^T_{it}	0.003 (0.00004)	−0.001 (0.0002)						
D^E_{it}	0.039 (0.00005)	0.062 (0.0002)						
$D^T_{i,t-1}$			0.0005 (0.00001)	0.001 (0.00003)			−0.009 (0.00002)	−0.009 (0.0001)
$D^E_{i,t-1}$			0.003 (0.00001)	0.006 (0.00003)			0.0001 (0.00002)	0.001 (0.0001)
u_{it}	−0.412 (0.001)	−0.470 (0.004)	−0.044 (0.0001)	−0.055 (0.001)			0.308 (0.0004)	0.327 (0.002)
$u_{i,t-1}$	−0.091 (0.001)	−0.171 (0.004)						
pl_{it}	−0.166 (0.001)	−0.201 (0.003)	0.007 (0.0001)	0.005 (0.0004)			−0.029 (0.0002)	−0.050 (0.001)
$pl_{i,t-1}$	−0.032 (0.001)	−0.045 (0.003)						
$D^U_{i,t-1}$					0.0002 (0.0001)	−0.019 (0.0003)		
mig_{it}			−0.005 (0.0002)	−0.007 (0.001)	0.041 (0.001)	0.033 (0.004)	0.138 (0.001)	0.149 (0.002)
Observations	13,757,289	923,671	14,200,546	922,051	3,610,067	175,924	14,448,665	897,952
Adj. R^2	0.158	0.247	0.030	0.070	0.043	0.061	0.094	0.093
Res. SE	0.822	0.814	0.140	0.152	0.321	0.313	0.356	0.369

Table 4: Linear regressions for key outcomes using observed (Obs) and simulated (Sim) data for female sample and model.
Note: Standard errors are presented in parenthesis beneath estimated coefficients. Conditions for selection are based on rounded predictions for the simulated data.

5.2.2 Comparing predicted and observed means for key variables

In this section the fit of the model is evaluated by comparing life-cycle statistics observed in the data with those generated by the model. The model fit to male data will be presented in Figure 1 and the fit for females in Figure 2. Looking at Figure 1, the model seems to fit the transition rates for males relatively well. The frequency of unemployment to employment transitions and job changes are predicted accurately by the model. The simulated employment to employment transition rate is a bit below the observed one which translates into a slight underprediction of employment. Average earnings over the life-cycle are well captured by the model until the age of 45 where the predicted income levels are lower than those observed in the data. The model captures the accumulation of states over the life-cycle well and the shapes of the observed and simulated curves are similar.

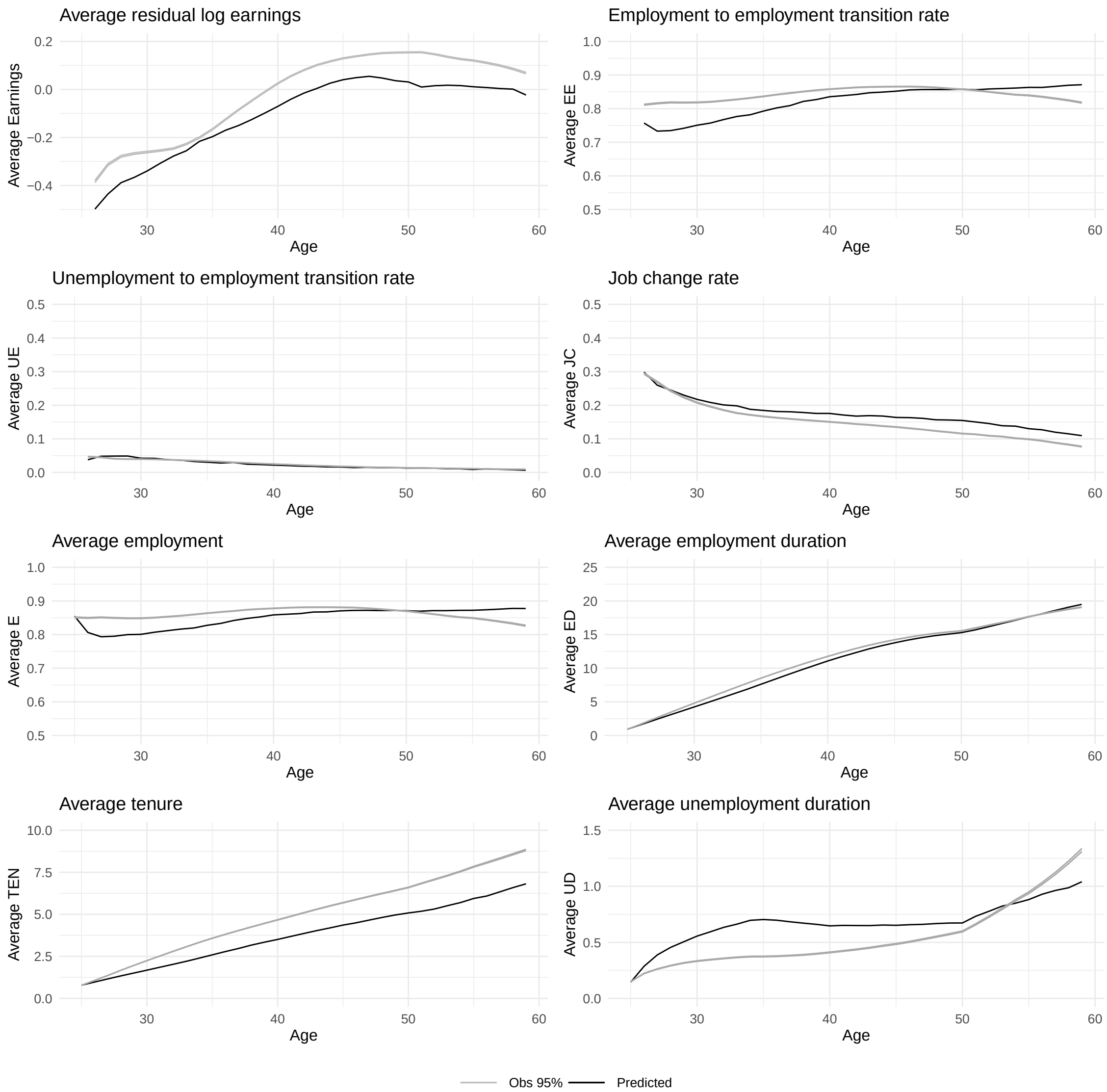

Figure 1: Fit of model over life-cycle for male workers.
Note: Observed statistics are presented as a 95% confidence interval around the mean.

Figure 2 shows the predicted and observed outcomes for females. Overall the model fits the data fairly well, the unemployment to employment and job change rates are well captured by the model, and average earnings are somewhat accurately captured over the life-cycle. The simulated employment to employment transition rate is less accurate than the male counterpart, in particular during the early years on the labor market. This translates into an underestimation of the overall employment levels during the first half of the working life. The aggregated accumulation of employment duration is well captured by the model while the other states are not as well predicted. Unemployment duration is slightly too high during the first half of the working life, this results from the underestimation of the employment to employment transition rate. Considering that these graphs show the prediction of 272 data points from a model with 49 parameters then the overall fit of the model is quite good.

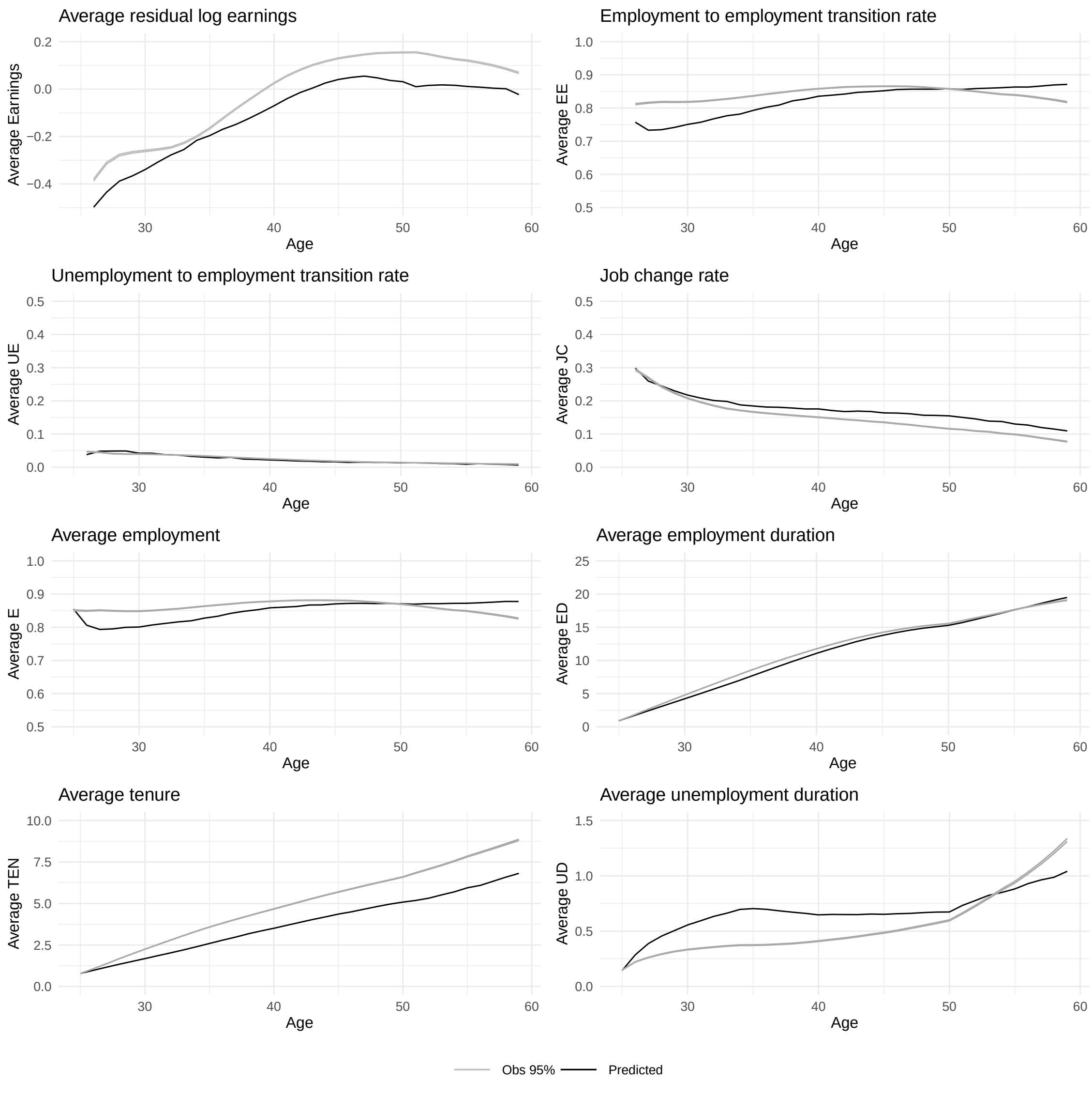

Figure 2: Fit of model over life-cycle for female workers.
Note: Observed statistics are presented as a 95% confidence interval around the mean.

To test the robustness of this simulation, we fit a model using samples of 100,000 individuals drawn from the data over the period 2002–2015. This means that labor market entry is not observed for all cohorts. Information on initial employment status, tenure, and employment duration can be obtained from the ASTRID data, which means that some initial conditions can be controlled for in this robustness check. However, this way of simulating the model does not allow for the accumulation of transitory shocks or job matches over the life-cycle for cohorts born before 1977, which affects the accumulation of transitory shocks and job-match heterogeneity. The resulting parameter estimates from this analysis are for the most part similar to the findings of the main analysis. Tables containing all parameter estimates can be found in Appendix D. The most interesting differences are that the robustness check estimates a lower persistence of productivity shocks, and a higher persistence for the job match process.

6 Applications

This section uses the model to address three key aspects of labor market dynamics and life-cycle earnings. The first application is an analysis of how large transitory shocks to unemployment risk affects the aggregate dynamics of key labor market outcomes. The second application focus on the accumulation and distribution of pension entitlements, and how it responds to unemployment occurring at different ages. In the final application, we look at how different aspects of the model contribute to life-cycle earnings inequality.

6.1 Unemployment risk

This application focuses on how a large temporary shock to unemployment risk affects aggregate earnings, employment, labor market mobility, and earnings risk. Using the data described in Section 4.1 and the parameter estimates from Section 5.1, we simulate the prime-age working life for the 100,000 men and women used in the estimation and calculate statistics for the period 2002–2015. These statistics are referred to as the baseline scenario, and they provide counterfactual references in absence of macroeconomic shocks. Then, we repeat the simulations this time adding an aggregate unemployment risk in 2005.[32] Three different sce-

[32]This year was chosen to allow a 10 year recovery period after the shock without having to extrapolate from the ASTRID data used in the estimation.

narios with varying levels of severity of the temporary macroeconomic shock were analyzed. These scenarios are a one-year 10%, 20% or 30% increase in unemployment risk. This risk affected both the currently employed, increasing the flow to unemployment and the currently unemployed by reducing the probability of finding new employment. The risk is the same for all individuals.[33] Figure 3 shows how these shocks affected the dynamics of aggregated earnings, earnings risk, employment, and labor market mobility.

The labor market recovers gradually after the shock to unemployment risk, the recovery is initially relatively rapid but tapers off after a few years. It seems like the labor market is returning to a new "equilibrium" path after an unemployment shock, part of the effects of the shock lingers 10 years after the event. The shock affects earnings the most in the long run. This can partly be explained by earnings being affected in two margins, both the latent earnings levels and the probability of employment are affected by the loss of experience. The long-run effect of the shock on employment and earnings is larger for men. Further calculations show that around 40 % of the initial shock to employment and around 46 % of the initial drop in average earnings lingers after ten years. For females, around 35 % of the initial shock to employment and 39 % of the initial shock to earnings remain after 10 years. However, females are more affected in terms of lingering earnings risk, around 44 % of the initial increase in the variance of earnings remains after 10 years. About 41 % of the effect remains after 10 years for males. The labor market mobility or job change rate recovers with a slight lag, as a successful employment to employment transition is necessary for a job change. However, this rate has recovered the most in the long run with only 25 (32) % of the initial shock remaining after 10 years for men (women).

[33] Another alternative would be to vary the additional risk by observable or unobservable characteristics, such as education or unobserved earnings ability.

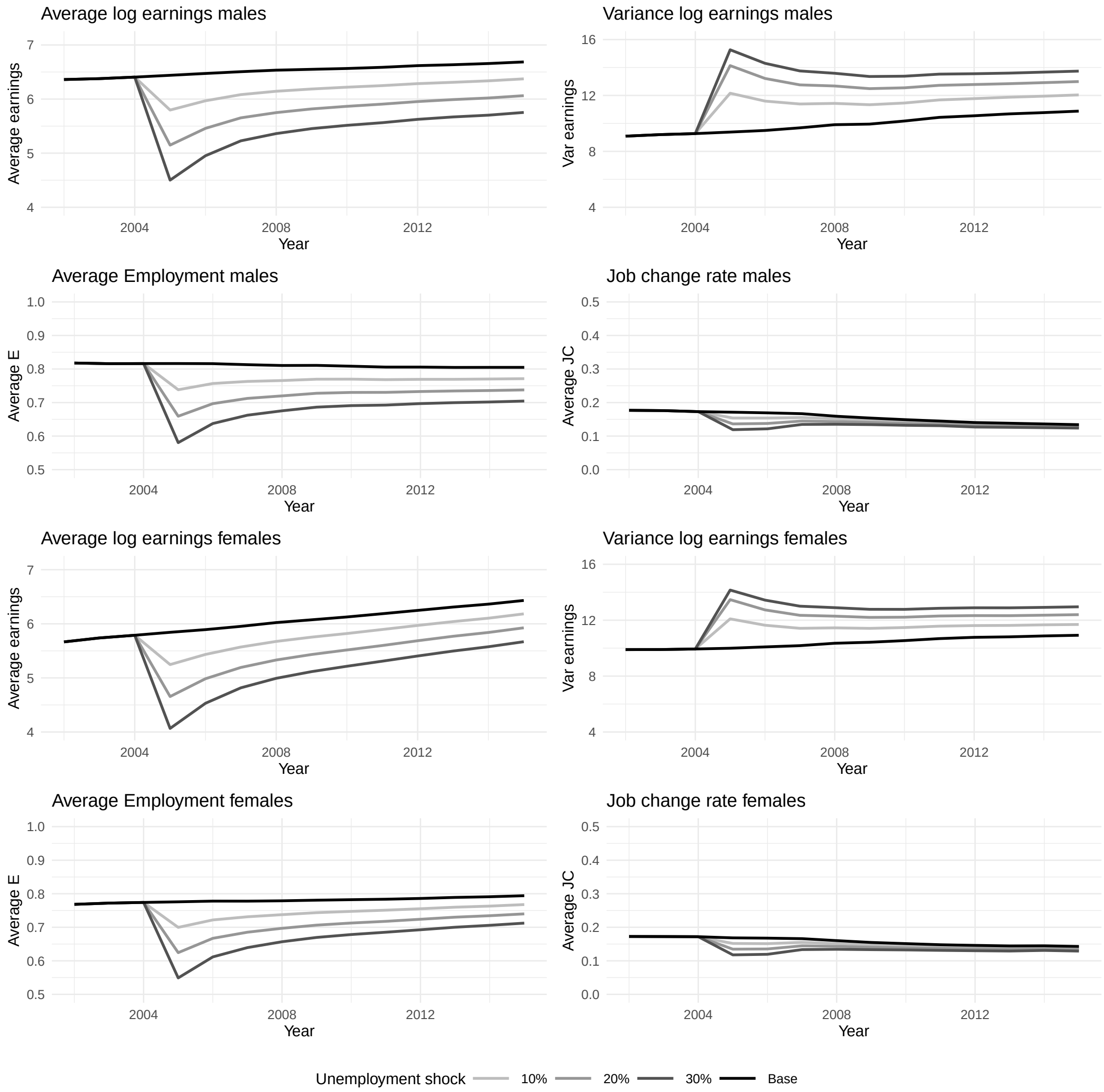

Figure 3: The effect of a temporary shock to unemployment risk on labor market outcomes.
Note: These graphs shows the effects of a one year 10/20/30 % increased risk of unemployment in 2005 for 100,000 men and 100,000 women born between 1956–1981.

From a policy perspective, this analysis suggests that temporary shocks to unemployment risk have large long-term costs in terms of foregone earnings and unemployment. To put this into perspective, there were 1,871,894 men and 1,755,141 women between 25-59 years working in Sweden in 2015. The average earnings level for this age group was 362400 SEK for men and 284700 SEK for women. If we include payroll taxes[34] and only consider this year, then a shock to unemployment risk of 10 % would result in a 123.6 billion SEK loss of value from the labor market. At the time, this corresponded to 2.9 % of the Swedish GDP. This is just

[34]Which is a 31.42 % add-on to all wage payments.

considering one year, 10 years after the events, and without considering any loss of profits for firms. These simulations support policy actions to combat unemployment in the event of a large-scale shock to unemployment risk to reduce the cost related to the loss of experience. This could, for example, be the implementation of furlough schemes or other types of support to firms to reduce the number of job losses.

The underlying mechanism behind the long-term effects of the shocks in this model is the loss of employment- and firm experience. If the firm- and employment experience depreciate rather than reset during unemployment, then the long-term effects of the shock would be reduced. At the same time, this analysis relies on the assumption that the labor demand and job allocation mechanisms are unaffected by the shock. This type of macroeconomic shock is likely to affect firms negatively. Another complication is that high levels of unemployment would increase the competition for vacancies between workers and add strains to both employment offices and staffing agencies. The disincentive effects of generous unemployment insurance are partially offset by the unemployment office's authority to withhold payments to individuals not exhibiting sufficient search efforts in Sweden, but high levels of unemployment could reduce their capacity to efficiently monitor the unemployed (Ljungqvist and Sargent, 1995). From this perspective then the cost of the shock may be underestimated.

6.2 Pension entitlements and unemployment

This section provides an analysis of the effect of unemployment at different ages has on the accumulation of pension entitlements over the prime-age working life. We study the 1970 cohort as their labor market entry in 1995 coincided with the implementation of a major reform of the Swedish pension system.[35] Sweden suffered from a deep economic recession in the early 1990s which triggered several reforms including the reformation of the pension system (Jonung, 2015). My analysis focuses on one component of the public pension scheme called the "income pension". The income pension constitutes the majority share of the public pension scheme and the annual rate of return on accrued pension entitlements is the same for all participants (Palmer et al., 2000). Many types of income contribute to the accumu-

[35] The reform became statutory 1999, but the revised pensions were calculated retroactively from 1995 and onward (Abelson et al., 2009).

lation of pension entitlements in Sweden. Therefore, we include an approximation of the Swedish unemployment insurance. Unemployment insurance is voluntary and managed by funds linked to trade unions in Sweden (Clasen and Viebrock, 2008). We provide further detail about the institutional background and social security systems in Appendix E.

This analysis required some additional information. A set of initial conditions and exogenous shocks were simulated for 50,000 men and 50,000 women born 1970.[36] The official statistics for average yearly earnings by gender for the age groups 25–59 (weighted by group size) between 1995–2019 were taken from Statistics Sweden.[37] Predictions for the years 2020–2029 were based on an extrapolation of a linear regression of mean earnings against nominal GDP per capita done separately for each gender. Real GDP per capita and predictions of future GDP per capita for the years 1995–2029 were taken from the model produced maintained by the Swedish National Institute of Economic Research.[38] Inflation measured by the consumer price index was taken from Statistics Sweden. From 2020 and onward, we assume a yearly inflation rate of 2%. The balance of the notational accounts[39] for income pension are adjusted at the start of each year by a factor based on the development of average income (in nominal terms) and the solvency of the pension system. These adjustments can therefore be both positive and negative.[40] For the years 1996–2020, we use the adjustments made by the Swedish Pensions Agency. The average yearly rate of return on the accumulated income pension balance (2.8 %) is used as the rate of return for the years 2021–2029. All incomes are therefore simulated in current prices before being deflated to 2018 prices at the end of the simulation routine.

Table 5 provides a comparison of characteristics of the actual and simulated income pension balances in Sweden in 2018 for the cohorts born in 1970. The model in this article only

[36]These were education level, initial employment status, migration, parental allowance, and unemployment benefits for all individuals over the period 1995–2029. The size of the simulation was reduced as only 56542 men and 53607 women were born in Sweden in 1970.

[37]The matrices HE0110K1 and HE0110K3.

[38]Downloaded this data 2020-08-04, these numbers are likely to be revised in the aftermath of COVID-19. However, this is unlikely to qualitatively affect the outcome of this analysis, as all individuals will face the same GDP level.

[39]As the income pension is a pay-as-you-go scheme current pension contributions are used to pay existing obligations. These accounts are used to keep track of individual contributions and accrued interest.

[40]More on this in Appendix E.

considers the prime-age working life and assumes labor market entry to occur at the age of 25. Individuals who entered the labor market at the age of 18 will have spent 30 years on the labor market instead of 23. Furthermore, we do not consider all possible sources of pensionable income; only income from labor and unemployment insurance payments. For example, parental benefits also contribute to pension entitlements but are not included in this simulation. This provides a possible explanation for the fact that the difference between the observed and simulated statistics is smaller for men than for women. This means that the simulations are likely to underestimate the accumulation of pension balance. The difference between the observed and simulated balance reduces when an approximation of the unemployment insurance is included in the simulation. The interquartile range of pension accumulations reduces when unemployment insurance is included.

	Males			Females		
	Real	UI	no UI	Real	UI	no UI
1st Quar.	700,759	655,594	511,490	801,694	505,337	285,998
Median	1,458,806	1,136,379	1,104,776	1,270,583	833,581	754,955
Mean	1,226,938	1,081,669	989,644	1,114,578	873,215	743,988
3rd Quar.	1,744,586	1,470,118	1,460,781	1,499,775	1,184,630	1,156,820

Table 5: Comparison observed and simulated income pension balance distribution for cohorts born 1970 in 2018.
Note: Labor market entry is assumed to occur at the age of 25 in the simulations and the simulations were done with and without unemployment insurance (UI).

Figure 4 shows the accumulation of pension entitlements over the prime working life for 50,000 individuals under different scenarios. The base-line case is the average accumulation of pension entitlements over the life-cycle as predicted by the model. The simulations are then repeated, this time forcing all individuals to become unemployed at a certain age to see how this affects the average accumulation of entitlements. Figures 5 and 6 show the distribution of pension entitlements at age 59 for college and non-college-educated workers, and how these distributions are affected by unemployment at different ages and by unemployment insurance. The model does not allow for behavioral responses to unemployment insurance. However, the unemployment insurance used is an approximation of the existing Swedish system.

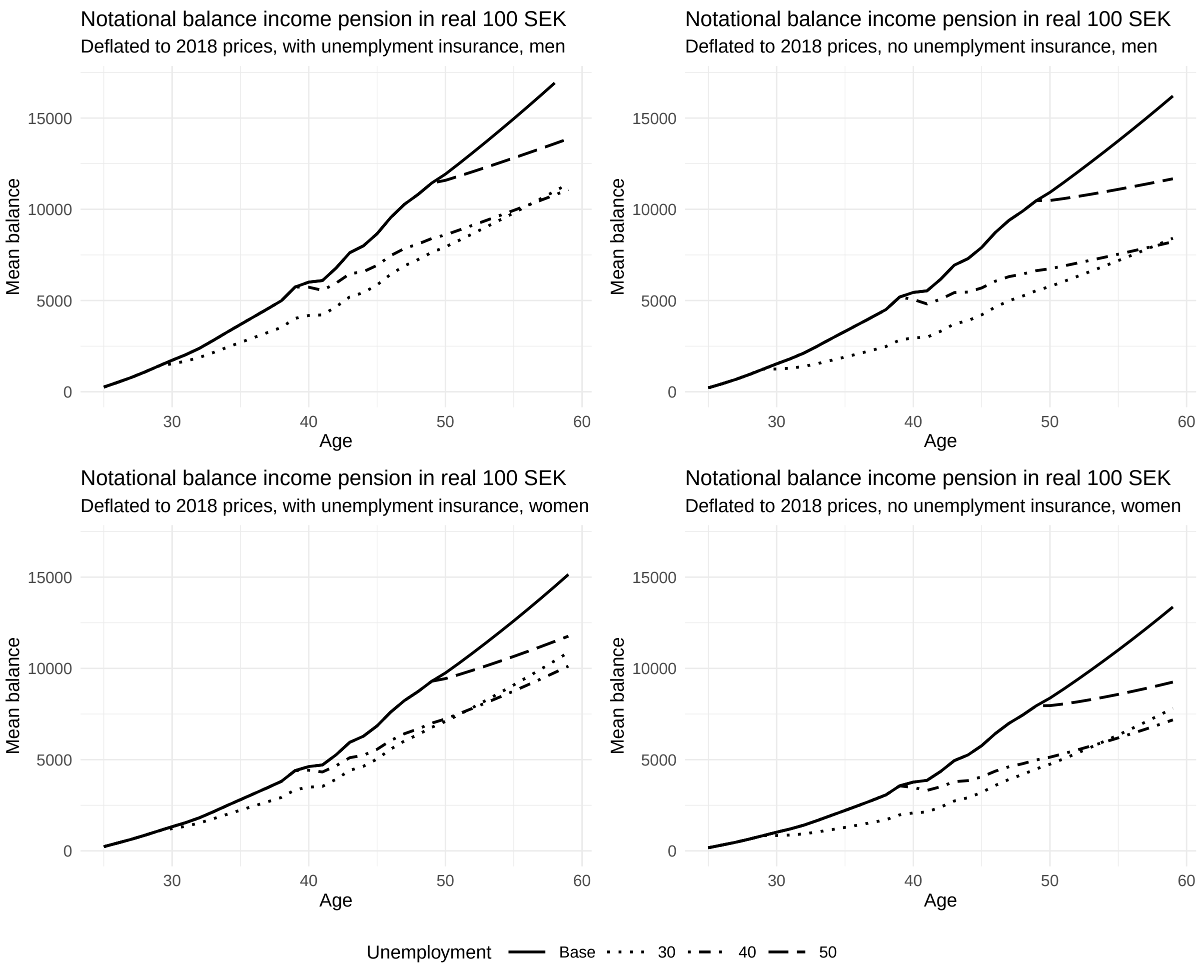

Figure 4: Income pension accumulation over the life-cycle for men and women, with and without unemployment insurance and the effect of unemployment at different stages of the working life.
Note: This graph shows the mean accumulation over the life-cycle for 50000 men and women simulated to have been born 1970.

From Figure 4, one can see that unemployment shocks at age 30 have a lower impact on life-cycle pension accumulations than shocks occurring at age 40 for both men and women. Female workers seem to recover better from an unemployment shock than men. When unemployment insurance is included, then the trend suggests that women becoming unemployed at 30 may accumulate more pension entitlements than those unemployed at 50. This will however depend on when they decide to retire. Workers unemployed at age 30 recover more than workers unemployed at age 40. The timing of the shock affects both how long the adverse effects of unemployment are allowed to accumulate as well as the length of the recovery period. This means that the life-cycle consequences resulting from the timing of an unemployment shock are not obvious. A shock early in the working life has a relatively low cost in terms of accumulated experience and provides a long recovery time with labor market activity. On the other hand, previously accumulated incomes will be unaffected by an unemployment spell at an older age. However, Merkurieva (2019) found that the difficulties of finding new employment for older workers who have lost their employment can trigger premature retirement. She found that displaced workers retire more than one year earlier on average compared to what they would have done if they had kept their employment. If unemployment shocks among older workers increase the risk of a permanent exit from the labor force, then this amplifies the negative impacts of old age unemployment on pension accumulation. However, the retirement decision goes beyond the scope of this paper.

Figure 5 present the distribution of pension entitlements at the age of 59 for men and women with and without a college education. From this, we find that workers with less education are more affected by unemployment shocks. Lesser educated benefit more from the inclusion of unemployment insurance into the pension entitlement accumulation. The bunching resulting from the unemployment benefits is more pronounced for women than for men. One can also see that there is a larger spread in pension balance among men than women, which is consistent with the observed pension statistics (see Table 5).

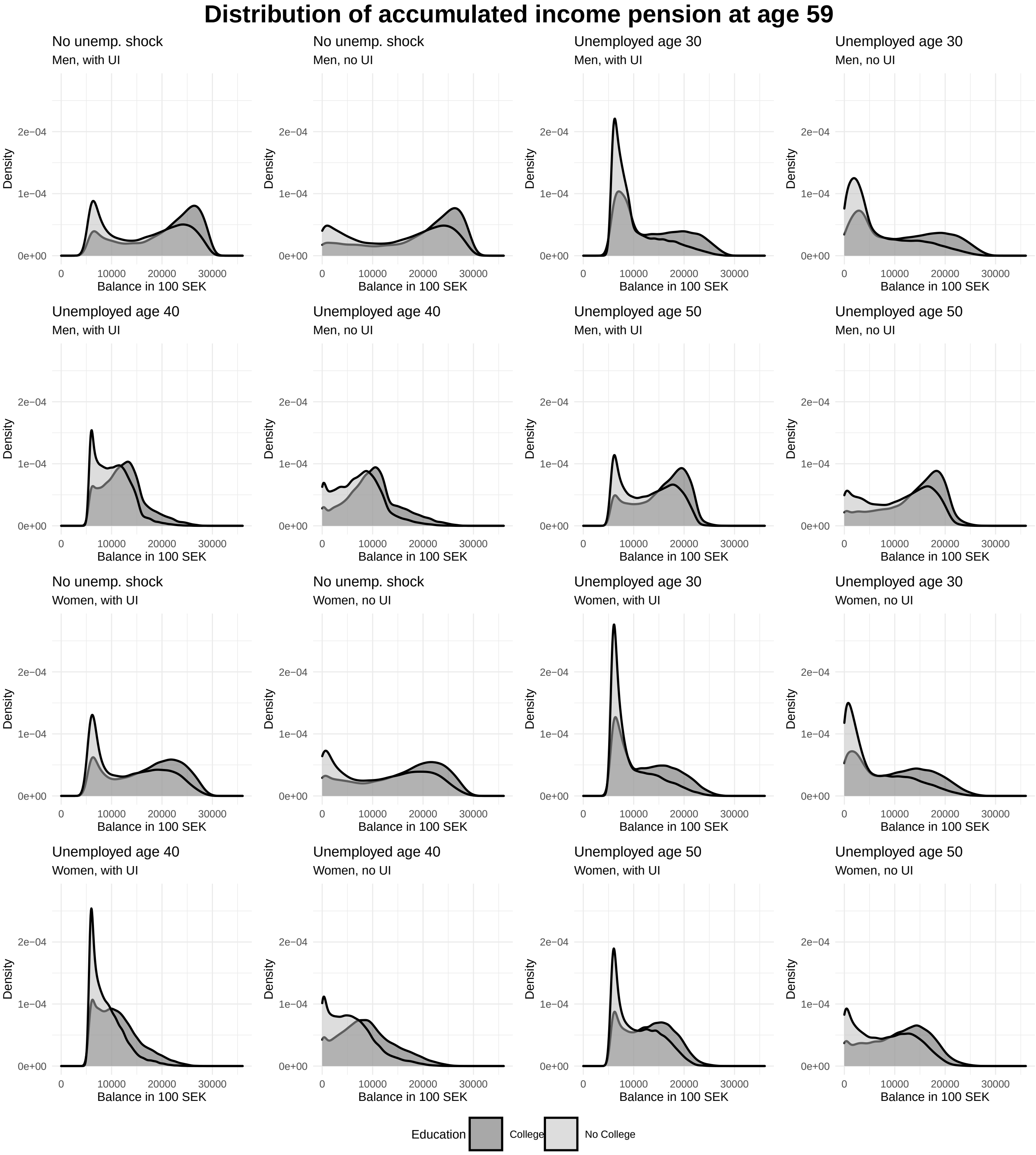

Figure 5: This figure shows the distribution of pension entitlements for men and women at the age of 59, with and without unemployment insurance (UI), including the effect of unemployment imposed at different stages of the working life.
Note: These simulations are based on the life-cycle incomes of 50,000 men and 50,000 women born in 1970. The pension balance is in 100 SEK deflated to 2018 prices.

6.3 Sources of earnings inequality

In this section, we use the model to measure how exogenous shocks and unobserved heterogeneity contribute to life-cycle earnings inequality. A baseline measure of inequality was created by simulating data for the accumulated earnings over the life-cycle for the 1970 cohort using the economic model and the estimated parameter values (see Section 5.1). This data is then used to calculate the mean and the variance of yearly earnings over the life-cycle. To test the impact of transitory earnings shocks (ω_{it}), unobserved individual ability (α_i) and propensity to change employer (η_i), the job match ($Match$), short unemployment spells (u_{it}), parental leave (pl_{it}) and migration (mig_{it}), accumulated earnings were simulated setting all the parameters corresponding to these different components to 0. Due to the non-linearity of the model then the relative contributions of the model do not sum to 1.[41] The results of this analysis are presented in Table 6.

	Males			Females		
	Mean	Var.	Norm.	Mean	Var.	Norm.
$Baseline$	7.563	3.417	1.000	7.313	4.257	1.000
ω_{it}	7.465	3.303	0.967	7.115	4.010	0.942
α_i	7.642	2.999	0.878	7.390	3.818	0.897
η_i	7.658	2.868	0.839	7.408	3.701	0.869
$Match$	7.360	3.123	0.914	7.086	3.882	0.912
u_{it}	7.846	3.147	0.921	7.526	4.101	0.963
pl_{it}	7.385	3.568	1.044	7.341	4.278	1.005
mig_{it}	7.549	3.563	1.042	7.310	4.330	1.017

Table 6: Estimated mean and variance yearly earnings over the life-cycle and variance normalized based on the baseline inequality.
Note: This simulation was done assuming a sample born 1970 being of prime working age between 1995–2029. The means and variances (Var.) were calculated on life-cycle earnings measured in 100 SEK in 2018 prices. Variances are also presented normalized using the baseline scenario as reference (Norm.).

We find that unobserved propensity to change employer contributes the most to life-cycle earnings inequality followed by unobserved ability. This is true for both men and women and

[41] Altonji et al. (2013) did a second order normalization so that the contributions in their decomposition added up to 100%.

suggests that individual differences are an important factor behind the observed earnings inequality. The job match process is the third most important contributor. Short unemployment shocks and productivity shocks make important contributions as well. However, their relative importance is different for men and women. The productivity shocks contribute more than unemployment for women and vice versa for men. Removing short spells of unemployment have a relatively large positive effect on average life-cycle earnings for both men and women. The table also shows that migration and parental leave shocks reduce earnings inequality within this modeling framework.

7 Conclusion

This paper aims to present a model of earnings dynamics including labor market transitions building on the model of Altonji et al. (2013) and to estimate it using Swedish register data. This model is then used to analyze several economic problems. First, we analyze the effects of temporary shocks to unemployment risk have on the dynamic behavior of the labor market. Second, how unemployment at different ages affects the accumulation and distribution of pension entitlements. Finally, we analyze how different parts of the model contribute to life-cycle earnings inequality.

We find that temporary shocks to unemployment risk have large and long-lasting effects on the labor market. Simulations showed that the annual cost of a 10 % shock to unemployment risk in terms of foregone wage payments corresponded to 2.9 % of the Swedish GDP 10 years after the event. This provides support for active labor market policies aimed to reduce job losses after sudden shocks to unemployment risk. An example of this could be furlough schemes during pandemics.

We also find that unemployment, in particular during the middle ages, has severe effects on the accumulation of pension entitlements. The pension entitlements of women and low educated workers are most adversely affected by these unemployment spells. Linking unemployment insurance payments to pension contributions increases the pension balance for low-income earners and reduce the spread of the distribution. Another finding was that unobserved individual heterogeneity and job match heterogeneity can explain a large share of the observed life-cycle earnings inequality.

Many of the estimates from this analysis, such as the returns of education to earnings and the level of persistence of transitory shocks to earnings are similar to those found in previous literature using Swedish data.[42] This while the model manages to capture multiple aspects of the labor market as well as inter-dependency between the different labor market processes in a richer framework. The modeling framework used in this paper can be expanded in many directions. It would be possible to include business cycle properties into the model with some additional data. Other worthwhile extensions would be making fertility or migration decisions endogenous, increasing the frequency of the simulation to better capture the role of short-term unemployment, including more labor market states such as self-employment, or including individual labor market entry and exit decisions. These extensions go beyond the scope of this paper.

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[42] Isacsson (1999); Björklund (2000) found similar estimates on the returns to education in Sweden. For the persistence of transitory shocks to earnings Gustavsson (2007, 2008) and Gustavsson and Österholm (2014) estimated a similar level of persistence for transitory shocks to earnings of Swedish males.

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Appendix A: An introduction to indirect inference

Assume a general economic model that has the following form:

$$y_t = f(y_{t-1}, x_t, u_t; \theta), \quad t \in [1,\ T] \tag{1}$$

Where y_t is a $T \times 1$ vector of dependent variables, x_t is a matrix of $T \times k$ exogenous variables, u_t is a $T \times 1$ vector of unobserved random errors and θ is a $k \times 1$ vector of parameters. If the errors are independent and identically distributed with a known probability distribution and the initial condition (y_0) is known, then the economic model gives a conditional probability function for the vector of dependent variables. A common problem for economic models is that this conditional probability can be difficult (or impossible) to solve analytically. Indirect inference provides a possible solution to this problem as it does not require a correct specification of the conditional probability function. As long as it is possible to simulate data from the underlying economic model, then it is in principle possible to estimate almost any model using numerical simulations. This is where the intermediary statistic or "auxiliary model" becomes useful. This model does not have to provide an accurate description of the conditional probability for the dependent variables, it just has to capture certain key properties of the data. One can therefore specify a model that is more analytically tractable than the economic model. Once this auxiliary model is defined, one can estimate its parameters using both the real and simulated data.

$$\hat{\beta} = arg\,\max_{\beta}\, \mathcal{L}(y_t; y_{t-1}, x_t, \beta) \tag{2}$$

In this equation then $\hat{\beta}$ is a $p \times 1$ vector of parameter estimates using the observed data where the number of auxiliary parameters must weakly exceed the number of "structural" parameters ($p \geq k$).

Then one simulates a fixed set of unobserved errors and generates data using the economic model. This is typically done M times resulting in M statistically independent data sets $\tilde{y}_m$. The repeated simulations allow for control of the simulation error (Smith, 1993). One then estimates the parameters of the auxiliary model using these simulated data sets and commonly takes the average of these as the vector of simulated auxiliary parameter estimates $\tilde{\beta}$.

$$\tilde{\beta}(\theta) = \frac{1}{M} \sum_{m=1}^{M} arg\,\underset{\beta}{max} \sum_{t=1}^{T} \mathcal{L}(\tilde{y}_{m,t}(\theta); \tilde{y}_{m,t-1}(\theta), \tilde{x}_t, \beta) \tag{3}$$

Since the data generating process is dependent on the parameter values for the underlying economic model $\tilde{\beta}$ is implicitly a function of θ. This bridge relationship between the auxiliary and economic model[1] is implicitly defined by the parameters of the underlying economic model. One can then estimate the parameters of interest using some kind of objective function, such as a likelihood function.

$$\hat{\theta} = arg\,\underset{\theta}{max}\, \mathcal{L}\big(y_t; y_{t-1}, x_t, \tilde{\beta}(\theta)\big) \tag{4}$$

By maximizing this likelihood, one obtains an indirect estimate of the structural parameters ($\hat{\theta}$).

[1]The binding function using the terminology of Gourieroux et al. (1993).

Appendix B: Starting values

	Males	Females
$Constant$	-1.191	-1.191
$Education$	0.038	0.045
xp	-0.440	-0.189
xp^2	-0.156	-0.224
TEN_{it}	0.003	0.004
ED_{it}	0.044	0.038
u_{it}	-0.562	-0.406
$u_{i,t-1}$	-0.198	-0.087
pl_{it}	0.035	-0.171
$pl_{i,t-1}$	-0.010	-0.035
θ_{α}^{earn}	0.100	0.191
ρ_m	0.500	0.500
θ_m^{earn}	0.100	0.100
ρ_{ω}	0.796	0.707
σ^{earn}	0.132	0.291
σ_0^{earn}	0.990	1.601

Table 1: Starting parameter values for estimation of latent log earnings for male and female workers.

	Males			Females		
	E^E	U^E	JC	E^E	U^E	JC
$Constant$	1.263	-0.846	-0.817	0.895	-1.191	-0.986
$Education$	0.012	0.028	0.007	0.038	0.037	0.019
xp	-0.626	-0.517	-0.292	-0.291	-0.599	-0.305
xp^2	0.142	0.169	0.051	0.047	-0.019	0.036
xp^3	-	-	-0.072	-	-	-0.049
$TEN_{i,t-1}$	0.024	-	-0.057	0.022	-	-0.055
$ED_{i,t-1}$	0.065	-	-0.001	0.063	-	-0.001
$UD_{i,t-1}$	-	-0.070	-	-	-0.074	-
u_{it}	-0.716	-	0.990	-0.483	-	0.884
pl_{it}	0.622	-	-0.063	0.115	-	-0.111
mig_{it}	-0.105	0.278	0.451	-0.076	0.137	0.451
$\theta_{m,t-1}^{JC}$	-	-	-0.100	-	-	-0.100
θ_{ma}^{JC}	-	-	0.100	-	-	0.100
θ_{α}	0	0	0	0	0	0
θ_{η}	0	0	0.100	0	0	0.100

Table 2: Starting values for transition equations for males and females.
Note: Standard errors are presented in brackets.

Appendix C: Marginal effect final transition for the 1970 cohort

The estimated marginal effects for transition probabilities can be found in Table 3. These are calculated from the final transition rate for 50,000 men and women born in 1970. This provide a measure of the marginal effect of different variables. For the variables related to unobserved heterogeneity, then marginal effects were measured by comparing the outcome with and without adding one standard deviation to the heterogeneity measure. The findings are presented as the percentage point change of the transition probability following the change in treatment.

	Males			Females		
	E^E	U^E	JC	E^E	U^E	JC
Education	0.022	0.062	0.078	0.018	0.040	0.254
$D^T_{i,t-1}$	0.054	-	-0.604	0.014	-	-0.664
$D^E_{i,t-1}$	0.094	-	-0.026	0.042	-	-0.018
$D^U_{i,t-1}$	-	-0.140	-	-	-0.036	-
u_{it}	-2.194	-	16.182	-0.828	-	18.564
pl_{it}	0.658	-	-0.970	0.014	-	-2.366
mig_{it}	-0.302	0.626	6.236	-0.112	0.150	8.104
α	0.440	-0.356	0.340	0.204	-0.152	0.476
η	0.094	0.640	3.204	-0.016	-0.200	2.102
$m_{if't}$	-	-	4.472	-	-	6.372

Table 3: Marginal effects on final transition in percent for males and females born 1970.

The simulated marginal treatment effects found in Table 3 follow the same pattern as the parameter estimates found in Table 2 but facilitates the interpretation of the parameters as the marginal effect of a variable on the individual transition probability depends on the sum of all other components of the equation. For example, from Table 3 we can see that if all individuals were hit by a temporary unemployment shock at the age of 58 the job change rate in the population would increase by 16.1 (18.6) % for men (women).

Appendix D: Robustness check simulation of exogenous shocks

	Males	Females
$Constant$	-1.324	-1.452
$Education$	0.025	0.048
xp	-0.790	-0.369
xp^2	-0.192	-0.229
TEN_{it}	0.002	0.012
ED_{it}	0.058	0.048
u_{it}	-0.724	-0.533
$u_{i,t-1}$	-0.284	-0.195
pl_{it}	0.058	-0.211
$pl_{i,t-1}$	0.008	-0.063
θ_{α}^{earn}	0.389	0.404
ρ_m	0.359	0.339
θ_m^{earn}	0.437	0.398
ρ_{ω}	0.156	0.268
σ^{earn}	0.314	0.553
σ_0^{earn}	0.590	1.221

Table 4: Parameter estimates robustness check for latent earnings for males* and females.

*Note: Estimated using exogenous shocks and initial conditions from 100,000 individual samples for the period 2002–2015. *Still running.*

	Males			Females		
	E^E	U^E	JC	E^E	U^E	JC
$Constant$	1.246	-1.034	-0.878	1.012	-1.463	-1.031
$Education$	0.032	0.015	0.013	0.037	0.050	0.020
xp	-1.028	-0.751	-0.357	-0.237	-0.606	-0.360
xp^2	-0.071	0.124	-0.044	0.019	0.003	-0.004
xp^3	-	-	-0.144	-	-	-0.073
$TEN_{i,t-1}$	0.033	-	-0.062	0.031	-	-0.050
$ED_{i,t-1}$	0.075	-	-0.002	0.073	-	-0.001
$UD_{i,t-1}$	-	-0.080	-	-	-0.084	-
u_{it}	-1.227	-	1.230	-0.876	-	1.046
pl_{it}	0.791	-	-0.064	-0.045	-	-0.181
mig_{it}	-0.195	0.318	0.506	-0.117	0.177	0.501
$\theta^{JC}_{m,t-1}$	-	-	-0.410	-	-	-0.323
θ^{JC}_{ma}	-	-	0.341	-	-	0.347
θ_α	0.715	-0.390	-0.163	0.403	-0.372	-0.035
θ_η	0.012	0.389	0.334	0.034	0.382	0.333

Table 5: Preliminary parameter estimates robustness check for transition equations for males* and females.

*Note: Estimated using exogenous shocks and initial conditions from 100,000 individual samples for the period 2002–2015. *Still running.*

Appendix E: Background for pension application

Sweden suffered from a deep economic recession in the early 1990s which led to several reforms such as an overhaul of the fiscal framework including the establishment of a surplus target of 1% over the business cycle (Jonung, 2015). This also triggered a reform of the Swedish pension system which resulted in a new set of rules regulating earnings-based old age pensions being implemented in 1999 (Abelson et al., 2009).[2] The pre-existing pay-as-you-go defined benefit system was replaced by a pay-as-you-go notational defined contribution system[3] (income pension), a privately managed advance funded second pillar (premium pension) and a guaranteed pension designed to ensure the lifetime-poor (Palmer et al., 2000). It is common for Swedish employees to be covered by collectively bargained group pension insurances as well. These insurance schemes are negotiated locally and vary in their designs and contribution rates. At the end of 2000, most non-state employed employees were covered by some kind of privately managed advance funded defined contribution collectively bargained insurance with contribution rates around 2–4.5% of earnings (Palmer et al., 2000). The application in this paper focuses on one component of the pension system, the income pension, which constitutes the largest share of the public pension scheme and has a homogeneous rate of return.

Yearly contributions to the pension system are 18.5% of "pensionable income" which consists of labor income as well as social insurance payments, such as unemployment insurance. 16% contributes to the income pension balance and 2.5% to the premium pension savings. The contribution is 93% of pensionable income up to a limit of 8.07 "income base amounts".[4] I obtained data for income base amounts for the years 1995–2020 from Statistics Sweden. I extrapolated these values between 2020–2029 assuming

[2]Pension accumulations were calculated retroactively from 1995 using the new system.

[3]This mean that the contributions to the system are used to pay current pensions, that these contributions are stored in notational accounts rather than in assets or accounts and that the system states what a worker should contribute rather than what pension she or he will receive when retiring.

[4]This is a measure used for pension calculations updated each year based on the economic developments in Sweden.

the same growth rate as nominal GDP per capita. The contributions to the income pension add to the balance of the workers' notational account[5] while the contributions to the premium pension contribute to individual savings in funds[6]. The balance of the notational accounts for income pension is adjusted at the start of each year by a factor based on the development of average income and the solvency of the pension system, these adjustments can therefore be both positive and negative. For the years 1996–2020 I use the actual adjustments made by the Swedish Pensions Agency. The predicted future adjustments for 2021–2029 are the historical average with a 2.8 % yearly rate of return on the accumulated balance.

Social insurance payments also contribute to pensionable incomes in Sweden. I include an approximation of the unemployment insurance in the simulation of life-cycle pension contributions to partially account for the distributional effects of this. Unemployment insurance is voluntary in Sweden and administered by trade union-linked funds (Clasen and Viebrock, 2008). The reimbursements received upon unemployment are based on previous income. Between 1995–2020 the reimbursement rates, maximum daily insurance payment, and basic coverage have been frequently changed. The initial reimbursement rate has for all years but 1996[7] been 80% of the previous wage up to a nominal ceiling of 564–910 SEK per day. The full basic coverage has varied between 245–365 SEK per day. I use data on the maximum limits from the Swedish Unemployment Insurance Inspectorate (IAF) to approximate unemployment insurance between 1995–2020. From 2021 and onward I assume that the limits for the unemployment insurance are adjusted following the growth in nominal GDP per capita.[8] This UI-approximation will only cover full-year unemployment as determined by the model. Within-year short unemployment shocks are not covered. I also assume that all workers have a UI membership and fulfill all requirements for receiving benefits whenever they

[5]Since the income pension is a pay-as-you-go system the contributions are used to finance current pension payments.

[6]These funds can be privately or publicly managed depending on the investment choice of the worker.

[7]The replacement rate was 75% in 1995.

[8]Historically these limits have changed at a lower frequency.

are long-term unemployed. This simulation does not include all types of incomes and benefits that contribute to pensionable income, but yearly earnings and unemployment benefits contribute to a large portion of the pensionable income for most employees.