# Earnings and Employment Dynamics: Capturing Cyclicality using Mixed Frequency Data

Johan Holmberg*

June 2021

**Abstract**

In this paper, we present a model of earnings dynamics that includes transitions in and out of employment as well as business cycle fluctuations. The model is estimated using the method of indirect inference and a mix of Swedish register, survey, and macro data. We find that the business cycle has a larger effect on transitions from unemployment to employment than on the risk of becoming unemployed. By simulating data from the model, we find that the business cycle has a relatively small impact on earnings inequality in Sweden and that women's labor market outcomes are less sensitive to business cycle fluctuations compared to men's. Finally, we find that economic crises have a more severe impact on young workers.

***Keywords:*** Earning dynamics, Unemployment, Business cycles, Inequality

## 1 Introduction

In this article, we examine the relationship between business cycle fluctuations and both life cycle employment and earnings inequality. To this end, we present a model of individual earnings and employment dynamics that also incorporates macroeconomic developments in the labor market. The model is estimated using the method of indirect inference and a mix of Swedish register, survey, and macro data. We analyze how business cycle fluctuations affect the employment and earnings of men and women, how these fluctuations contribute to earnings inequality in Sweden, and how economic crises of different lengths affect key labor

*Umeå University, e-mail: johan.holmberg@umu.se. This draft is preliminary, please do not redistribute or cite. First, I wish to express my gratitude to Gauthier Lanot, Thomas Aronsson, Giovanni Forchini, Michael Simmons, Katharina Jenderny and Johan Lundberg for their valuable input during the writing process as well as seminar participants at Umeå University, and the Scandinavian PhD Webbinar series. 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.

market outcomes. Understanding the sources of earnings inequality and unemployment over the business cycle is crucial for designing and evaluating policies aimed at reducing inequality and cyclical variations in employment. A second objective of this paper is to analyze the extent to which business cycle fluctuations affect the results of earnings dynamics models with labor market transitions, and to consider what could be done to control for these effects.

The literature studying why unemployment rises in recessions and falls in times of economic expansion is large (e.g., Darby et al., 1986; Blanchard and Diamond, 1990; Elsby et al., 2009; Fujita and Ramey, 2009; Shimer, 2012). A particular focus of this literature is whether the propagating forces behind changes in unemployment over time are fluctuations in the separation rates for the employed, variability in the search frictions for individuals looking for new employment, or a mixture of both. The view regarding which channel dominates has changed over time. Darby et al. (1986) and Blanchard and Diamond (1990) found that the variability in separations over time is the main driving force behind cyclical unemployment. Others, such as Shimer (2012) and Hall (2005b), have found instead that variations in the job-finding rate propagate the unemployment fluctuations and that the separation rate for the employed is more or less stationary over the business cycle. Several articles argue that both margins are relevant (e.g., Yashiv, 2007a,b; Fujita and Ramey, 2009; Elsby et al., 2009; Fujita, 2011), although the relative importance of the different margins is not definitively settled.[1] Policies aimed at preserving jobs during recessions are likely to be more effective in reducing unemployment if cyclical unemployment is the result of variations in the separation rates over time. Worker retention policies have been widely adopted among the OECD countries as a way of reducing the labor market effects of the Covid-19 lockdown (Scarpetta et al., 2020).

Similarly, understanding the dynamic properties of earnings is a topic of extensive study (e.g., Lillard and Willis, 1978; Lillard and Weiss, 1979; MaCurdy, 1982; Moffitt and Gottschalk, 1995). A recent strand within this literature has incorporated labor market transitions into

[1] For example, Fujita and Ramey (2009) argues that the separation margin is more important, as increases in job-finding rates tend to be preceded by an increase in separations. Meanwhile, Gorry et al. (2020) and Simmons (2020) find fluctuations in job-finding rates to be the more important margin.

the modeling framework (e.g., Low et al., 2010; Altonji et al., 2013; Friedrich et al., 2019; Holmberg, 2021; Card and Hyslop, 2021). In practical terms, allowing for transitions between employment and unemployment makes it possible both to handle unemployment in the analysis and to follow people over their whole labor market histories. These studies have shown that labor market transitions are relevant for the dynamic properties of earnings.[2] The common practice for dealing with business cycle effects within the earnings dynamics literature is to analyze residual earnings. One method for eliminating the effects of common shocks[3] is to subtract the yearly means from log earnings. However, when labor market transitions are introduced into this framework, the business cycle will reappear through its effect on employment. Explicitly including the business cycle in the modeling framework allows us to quantify its effect on earnings inequality. Our model also allows us to evaluate how individuals with different characteristics are affected by economic crises. It is important to consider the effects of individual differences, as the dynamic behavior of unemployment predicted using representative agent models and models including individual heterogeneity can differ substantially (Ahn and Hamilton, 2020). Gulyas and Pytka (2020) found that changes in the composition of workers losing their jobs during recessions contribute substantially to how the expected cost of a job loss changes over the business cycle. Understanding how different groups are affected by the business cycle is important: if certain groups are more exposed to these fluctuations, it is important to consider targeted policies to help these groups during economic crises.

Equilibrium search models (e.g., Mortensen, 1970; Pissarides, 1985; Mortensen and Pissarides, 1994) provide the leading theory of equilibrium unemployment. However, the standard formulation of these models with wage-setting based on Nash bargaining has been found to struggle to generate satisfactory levels of employment volatility over the business cycle (Shimer, 2005).[4] Although the standard search models are equilibrium models, some have studied the interaction between the business cycle and the labor market search (e.g.,

[2]For example, Low et al. (2010) found that a large proportion of observed wage shocks can be explained by individuals changing employers to find better matches and that the variability of permanent shocks is reduced when one accounts for endogenous transitions.

[3]Such as inflation or the business cycle.

[4]Hall (2005a) found that allowing for nominal rigidities in wages increases the business cycle fluctuations in unemployment generated by a search model.

Merz, 1995; Andolfatto, 1996; Christiano et al., 2016). This literature has combined real business cycle models and general equilibrium models to incorporate search and macroeconomic shocks, such as changes in monetary policy. One finding from this literature is that combined search and business cycle models are better equipped to capture certain realities, such as the fact that labor productivity is more volatile than real wages.

The composition of the workforce is likely to change over time. (Gorry et al., 2020) presents a labor market model in which agents have different experience levels, affecting both the probability of remaining in employment when employed and the probability of finding new employment when unemployed. In their model, labor market experience can be gained when working and lost when becoming unemployed. The unemployment rate will therefore depend on the composition of experience within the workforce as well as the rates of flow into and out of employment. Compositional changes can function as a transmission mechanism of unemployment over the business cycle. We study the labor market transitions of a population at the individual level, which allows our model to capture and control for changes in the composition of the workforce over time. These include demographic changes following the decrease in birth rates or changes in education levels between cohorts. Analyzing transition probabilities at the individual level also allows us to capture dynamic interactions between the separation and job-finding rates. These dynamic interactions can arise as a result of depreciation in experience following job losses.

The register data used in this analysis comes from the ASTRID database, which includes socio-economic and geographical information for the Swedish population born from 1936–1997 over the years 2002–2015, recorded at an annual frequency. This data is combined with flow statistics from the Labor Force Surveys (LFS)[5] published quarterly by Statistics Sweden, and business cycle information from the resource utilization (RU) indicator.[6] Using higher-frequency data allows us to incorporate business cycle properties into the model. To match this higher data frequency, we develop an empirical model of quarterly earnings dynamics and labor market transitions. The model is estimated using the method of indirect inference,

[5]Arbetskraftundersökningarna (AKU) in Swedish.

[6]The RU indicator is a measure of the Swedish output gap published quarterly by the central bank of Sweden.

which is a generalization of simulation-based inference methods[7] first suggested by Smith (1990). The estimation procedure builds on that of Altonji et al. (2013) and uses a mix of likelihood functions and moments to identify the parameters of interest.[8]

The main finding of the paper is that the business cycle has a larger effect on the probability for the unemployed to find new employment than on the unemployment risk for the already employed. This supports the view that vacancy creation and search frictions are more important than job destruction in terms of cyclical changes in unemployment levels. We find that the business cycle has a relatively small impact on overall earnings inequality in Sweden. Both unobserved individual heterogeneity and shocks to productivity contribute more to earnings inequality than the business cycle does. We also find that the labor market outcomes of women are less sensitive to business cycle fluctuations than the outcomes of men. This could be related to differences in occupational choices between men and women. Finally, we find that economic crises have more severe consequences for younger workers.

This paper is organized as follows. The data is described in the following section. Section 3 introduces the model and the estimation method is discussed in Section 4. Results and model fit are presented in Section 5. In Section 6, we use the model structure and our parameter estimates to illustrate the applications of the model. Section 7 concludes the paper.

# 2 Data

The register data we use comes from the ASTRID database. This data set is longitudinal and includes information for 7,478,807 individuals observed over the years 2002–2015. This database links geographical and socioeconomic data with information from tax records for the Swedish population born from 1936–1997. It is recorded at an annual frequency and was

[7]For example, the simulated method of moments of McFadden (1989).

[8]The mixed data sampling (MIDAS) regression (e.g., Ghysels et al. (2006, 2007)) is another estimation method that uses mixed-frequency data. This time series method implements a weighted aggregation of high-frequency data to predict lower-frequency outcomes. MIDAS regressions have been used by Barsoum and Stankiewicz (2015) to forecast GDP growth, by Bangwayo-Skeete and Skeete (2015) to forecast tourism demand, and by Bessec (2019) to predict business cycle turning points. The approach used in this paper uses a mix of high- and low-frequency data to identify a high-frequency model which includes both discrete event and multiple outcomes.

compiled by Statistics Sweden (SCB). The ASTRID data is hosted by the Department of Geography at Umeå University (Stjernström, 2011). We use this data to obtain individual-level information on year of birth, sex, earnings, education, and employment histories.

The Labor Force Surveys (LFS) is a monthly survey that gathers labor market statistics in Sweden. Individuals in the sample are repeatedly interviewed every third month for two years. The LFS sample is a rotating panel in which 1/8 of the subjects are replaced each quarter. This structure makes it possible to calculate aggregated transition rates (or flow statistics) at a quarterly frequency for the Swedish labor market. These statistics have been published quarterly since 2006; however, the ASTRID data only stretches to 2015. The estimation is therefore concentrated to the 40 quarters of the period 2006–2015. Our analysis focuses on one age group within the LFS: individuals aged 25–54. Including all individuals fulfilling this criterion in the estimation has several consequences. First, it means that the set of analyzed cohorts changes over time and that we include cohorts born from 1952–1990 in different years. The analysis was conducted using samples including information for 2,471,157 men and 2,412,736 women. Figure 1 shows the employment and transition rates for men and women in the ASTRID sample and the LFS.

The flow statistics, disaggregated into age groups, include students and the self-employed. This means that we cannot distinguish between different forms of employment[9] and between students and workers in the analysis. Treating the self-employed and employees the same is problematic, as the life cycle labor market behaviors of each group have been found to differ in Sweden (e.g., Humphries, 2017).[10] Including students is problematic, as their studies are likely to affect their potential labor supply.

[9]We disregard sailors from the analysis, as they face special rules when declaring income. For example, they are allowed to make special deductions from their taxable income and have exceptions for their taxable benefits. Sailors, however, constitute a very small fraction of the Swedish labor force.

[10]There is also literature on firm formation, for example, Kihlstrom and Laffont (1979) and Laussel and Le Breton (1995), as well as on the choice to become an entrepreneur. This occupational choice has, for example, been studied within a search framework by Rissman (2003) and within a Roy framework by Jovanovic (2019).

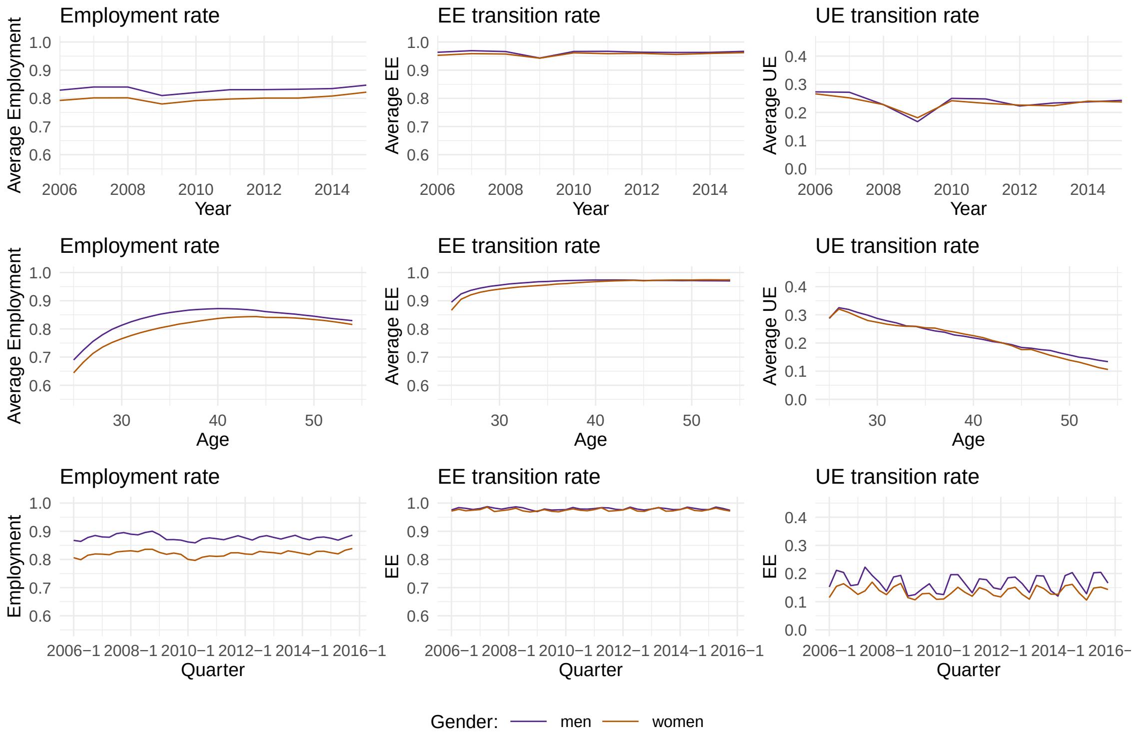


Figure 1: Employment and transition rates over calendar years, the life cycle, and quarterly by gender in Sweden 2006–2015.
*Note: EE denotes employment-to-employment transition rate among the employed while UE denotes unemployment-to-employment transition rate among the unemployed. The first two rows contain annual statistics from the ASTRID database while the bottom row contains quarterly statistics from the LFS.*

The business cycle data used in the analysis is the resource utilization (RU) index, published quarterly by the central bank of Sweden. This is an indexed estimate of the output gap measuring the difference between the realized and potential output of the economy. The measure combines survey data of the resource utilization within firms, gathered by the Swedish National Institute of Economic Research, with statistics on capacity utilization and labor market data from Statistics Sweden. The variables are chosen so as to capture the utilization of capital and labor as well as the current demand. We will henceforth refer to this as the output gap. During the quarters used in the estimations, this measure assumed values between $-1.743$ and $1.743$. The measure is constructed such that its mean is zero over the business cycle. More information on this measure can be found in Nyman (2010).

The register data provides information on the labor supply in Sweden as well as the composition of the labor force, while the flow statistics provide a measure of the matching on the labor market. Since the output gap captures information related to the use of productive resources in the economy, it provides some information on the demand side of the Swedish labor market. All individuals in the LFS can be found in the register data. Both measures of labor market status can be thought of as being generated by the same underlying labor market processes, albeit recorded at different frequencies.

Employment, unemployment, and non-participation in the labor force are elusive states from a statistical perspective. We define annual employment following the "gainful employment" definition used by Statistics Sweden for their register-based labor market statistics (RAMS). Statistics Sweden defines employment as having annual earnings exceeding a threshold level. This definition does not distinguish between the unemployed and those not participating in the labor force. The term "unemployed" will therefore be used to refer to all non-employed individuals. The LFS defines employment as either working a minimum of one hour during a reference week or as having employment but being absent from it during the reference week.[11] Threshold earnings levels (or limit amounts) used to distinguish between the employed and unemployed in RAMS are set to match the observed employment levels in the LFS. These thresholds are calculated using a model-based approach, which results in a discrepancy between the two statistical definitions of employment: in any given year, a set of individuals have mixed classifications and are defined as being employed in the register while being unemployed in the LFS, or vice versa (see Arvidson et al., 2005, for more details). This issue is further discussed in Section 4.1.

# 3 Model

The model presented in this section consists of a latent residual earnings process and two transition equations determining employment. It operates at a quarterly frequency and specifies the data-generating process used in the simulations. Both aggregated statistics of labor market flows and population-wide register data on the individual level are used when estimating the model. Some of the information generated by the model is therefore aggregated into the annual frequency during the estimation. The estimation procedure is further

[11]For example, due to sick leave or vacation.

discussed in Section 4.

All processes share a common set of variables, including years of education, a first- and second-order Chebyshev polynomial in potential experience,[12] the previous quarter's output gap[13] and unobserved individual heterogeneity $\alpha_i$. Individual heterogeneity is assumed to be fixed over time and to follow a standard normal distribution in the population. Normalizing the variance of the distribution facilitates the interpretation of our parameter estimates; an individual will have the same value of $\alpha_i$ in all parts of the models. In the following discussion, we will only mention the additional variables for each process.

We use residual earnings in the earnings process. These residuals are calculated by subtracting the yearly mean from log earnings. In the earnings dynamics literature, de-meaning log earnings is a popular method for removing common shocks from individual earnings (e.g., Baker and Solon, 2003; Kässi, 2014; Gustafsson and Holmberg, 2019).[14] The measure of earnings used in this analysis is the sum of labor income, including all taxable benefits, and positive income from own firm declared as wage income, both measured in 100 SEK. We use a wide definition of labor income, as we cannot exclude the self-employed from the analysis due to the limitation of the publicly available LFS statistics. We add 1 to the measure of earnings before making the log transformation to avoid any zeroes in the data. The earnings process is specified as follows:

$$earn_{iy} = \sum_{q=1|y}^{4|y} E_{iq} earn_{iq}^{lat}, \tag{1}$$

$$earn_{iq}^{lat} = X_{iq}^{earn} \theta_{earn}^{earn} + \theta_{\alpha}^{earn} \alpha_i + \omega_{iq}, \tag{2}$$

$$\omega_{iq} = \rho_{\omega} \omega_{i,q-1} + \epsilon_{iq}^{earn}. \tag{3}$$

Index $i$ refers to individuals, $y$ to year, and $q$ to quarter. Since the model operates at a quarterly frequency, annual earnings $earn_{iy}$ will be the sum of latent quarterly earnings $earn_{iq}^{lat}$

[12]Potential experience is measured as age minus years of education. We use Chebyshev polynomials as this restricts the values of the polynomial to between -1 and 1. This facilitates the interpretation of the coefficients as the underlying variation in the data will be comparable.

[13]To capture the impact of business cycle fluctuations.

[14]Regressions are also popular for calculating earnings residuals (e.g., Lillard and Weiss, 1979; Moffitt and Gottschalk, 1995).

realized through employment $E_{iq}$. This will capture some of the within-year variations in hours worked, but is not sufficient to isolate the effect of wage shocks. The earnings process also includes a third-order Chebyshev polynomial in potential experience, employment duration measured in years, and an AR(1) process capturing idiosyncratic shocks to productivity. The sign of the coefficient for unobserved heterogeneity $\theta_{\alpha}^{earn}$ is normalized to be non-negative to facilitate its interpretation across processes. This term can be thought of as unobserved individual earnings potential. We use a third-order polynomial in potential experience to better capture the life cycle pattern of earnings, while employment duration measures the importance of state dependence for earnings formation. In the earnings dynamics literature, the AR(1) process is a common way of capturing the impact of transitory shocks on earnings. The latent earnings process also includes the previous quarter's output gap to determine whether or not using the residual of log earnings remains sufficient to control for business cycle effects when labor market transitions are added to the earnings dynamics framework. If the de-meaning of earnings is sufficient for removing these effects, the estimated parameter of this variable should be close to zero.

Two transition equations determine employment: the transition from employment to employment $E_{iq}^{E}$ for the currently employed, and the transition to new employment $U_{iq}^{E}$ for the unemployed. These equations are indicator functions assuming the value 1 if the individuals successfully transition to employment from the previous state. This is a two-state model in which individuals are either employed or unemployed.[15]

$$E_{iq}^{E} = I\Big[X_{iq}^{E^E}\theta_X^{E^E} + \theta_{\alpha}^{E^E}\alpha_i + \epsilon_{iq}^{E^E} > 0\Big],\ if\ E_{i,q-1} = 1, \tag{4}$$

$$U_{iq}^{E} = I\Big[X_{iq}^{U^E}\theta_X^{U^E} + \theta_{\alpha}^{U^E}\alpha_i + \epsilon_{iq}^{U^E} > 0\Big],\ if\ E_{i,q-1} = 0. \tag{5}$$

The transition equations can be interpreted as conditional probabilities.[16] These processes

[15] An alternative approach is to use a three-state model, including a separate state for individuals not participating in the labor force. This type of framework has been used by, among others, Elsby et al. (2015), Simmons (2020) and Krusell et al. (2020). The definition of employment in the register data used for the estimation does not allow for the decomposition of the non-employed into unemployed and individuals not participating in the labor force. Shimer (2012) estimates both a two- and three-state model, but prefers the two-state versions.

[16] In this case, we can think of the $E^E$ transition as $P(E_{iq}^E = 1|X_{iq}^{E^E}, \alpha_i; E_{i,q-1} = 1)$ and the $U^E$ transition as $P(U_{iq}^E = 1|X_{iq}^{U^E}, \alpha_i; E_{i,q-1} = 0)$.

include an interaction term between level of education and being younger than 30. Publicly available statistics of labor market flows separated into age groups do not include any further disaggregation into education groups. The interaction term is included to partially control for the labor supply effects of individuals occupied with studies. The transition equations also include a set of dummies for the second to fourth quarters to capture seasonal effects, as well as a dummy for the years 2008–2009 to capture any additional effects from the financial crisis. The probability of remaining in employment for the employed also includes employment duration, measured in years. For the probability of finding new employment, a similar measure of unemployment duration is included. These durations are used to capture state dependence, or how the individual history of employment or unemployment affects the probability of future employment. The flow from employment to unemployment and from unemployment to employment determines quarterly employment:

$$E_{iq} = E^E_{iq} E_{i,q-1} + U^E_{iq}(1 - E_{i,q-1}). \tag{6}$$

An employed individual must either have remained in employment from previously being employed or returned to employment from an unemployment spell. The state in turn determines employment and unemployment duration in the following way:

$$D^E_{iq} = E_{iq}(0.25 + D^E_{i,q-1}), \tag{7}$$

$$D^U_{iq} = (1 - E_{iq})(0.25 + D^U_{i,q-1}). \tag{8}$$

Employment and unemployment duration are measured at an annual frequency. If the individual remains in a state, for an additional quarter 0.25 is added to their previous state. This measure resets if the individual switches state, i.e., if an unemployed individual finds new employment or an employed individual becomes unemployed.

# 4 Estimation

The interdependence between employment transitions, the unobserved heterogeneity, and the state dependence means that we cannot estimate the model using traditional methods such as maximum likelihood or GMM. Thus, we instead estimate the model using indirect inference, which is a generalization of simulation-based methods of inference (Smith, 1990). Indirect inference combines the use of intermediary statistics and computer simulations to produce an estimator of structural parameters. The intermediate statistics need not identify the parameters of interest directly, as is done in more traditional methods. The auxiliary model does not have to provide a consistent estimator for the parameters (Gourieroux et al., 1993). Instead, these statistics summarize the features of the data that we want to explain with the model. In practice, we specify an auxiliary model that captures dimensions of the data very similar to those we are trying to explain with our economic model. An auxiliary model can be formulated in such a way that it is possible to explicitly derive its likelihood function or theoretical moments. In a likelihood context, the density of the auxiliary model need not accurately describe the conditional density of our economic model.[17] Indirect inference makes it possible to estimate models that are too complicated for more traditional methods and allows us to substitute a likelihood without any closed-form solution with one that is similar but more practical to work with.

The estimation was conducted in two steps. In both steps, we used a mix of the numerical optimization package BB in R by (Varadhan and Gilbert, 2009) and a local search. We allow the optimization to take up to 40 quasi-Newton steps before performing a local search. In the first step, we used simulations, including 100,000 individuals observed over 40 quarters with two repetitions per function evaluation. The procedure was repeated 20 times. The second step used the preliminary estimates as a starting point and scaled up the simulation to include 10 repetitions per function evaluation. The procedure of numerical optimization and a local search was then repeated another 20 times. The estimation is extremely computationally demanding and the intertemporal dependencies between the different labor market processes limit the extent to which simulation can be parallelized. In the end, this meant that the estimation took several weeks to complete.

The binary outcomes of this model prohibit the use of gradient-based optimization algorithms, as discrete events cause the auxiliary statistics to be discontinuous in the parameters

[17]See Smith (1993).

of the economic model. We smooth the output from the transition equations and the gainful employment threshold using the smoothing procedure suggested by Keane and Smith (2003) and Bruins et al. (2018).[18] We modify the simulation process so that it produces output that is continuous in the model parameters. The smoothed output provides approximations to the discrete indicators. This approach produces consistent estimates so long as the auxiliary models for the real data and the simulations asymptotically converge to the same binding function. Standard errors were calculated using a bootstrap procedure.

## 4.1 Aggregation

The model generates data at a quarterly frequency, which we match with auxiliary statistics from the ASTRID data. Since these statistics are calculated annually, we must aggregate our simulated quarterly data. We do this by emulating the LFS. Recall that the definition of employment used in the RAMS is based on LFS data. Using a simulated survey allows us to keep our data-generating process close to the real production of statistics. We sample 8000 individuals from the simulated data each quarter. This sample is a rotating panel and, as with the LFS, we replace 1/8 of the subjects each quarter. The set of individuals included in the simulated survey is determined prior to simulating the data. Agents are only allowed to be included once for a maximum duration of eight quarters.

There is a known discrepancy between the annual employment levels as defined in the register data and the employment level of the LFS: the aggregated employment level in the LFS is in general around 2 percentage points higher than the corresponding levels found in the RAMS. We refer to Häkkinen Skans (2019) for further discussion of the different sources of Swedish labor market statistics and the discrepancies between them. In the estimation, we adjust for the observed difference in the aggregated annual employment rates for the 25–54 age group each year to control for the net classification error. We use the annual employ-

[18]Define $\hat{w}_{iy} = \bar{w}_y - w_{iy}$, where $\bar{w}_y$ is the threshold earnings for gainful employment year $y$ and $w_{iy}$ is the simulated annual earnings of individual $i$. The smoothed employment status year $y$ for individual $i$ will then be $e(\hat{w}_{iy}; \lambda) = \frac{1}{1+exp(\hat{w}_{iy}/\lambda)}$. The smoothing procedure introduces an approximation error into the model; it is therefore important to strike a balance between the bias that the smoothing factor generates and the smoothness of the objective. Following Altonji et al. (2013), we use a smoothing parameter $\lambda$ of 0.05.

ment rate from our simulated LFS to define yearly cut-off points for gainful employment. Agents must have earnings exceeding this limit to be considered employed during that year. This threshold was smoothed using the procedure from Keane and Smith (2003). Annual employment status was then used to define $E^E$ and $U^E$ transitions at a yearly frequency, and to provide annual measures of employment and unemployment duration. We also use the simulated LFS to calculate labor market flow rates, which we use in the estimation.

## 4.2 Auxiliary model

This section presents the auxiliary model used during the estimation procedure. The auxiliary model provides the lens through which we can compare the data generated by the model and the statistics we observe. Since the parameter estimates of the auxiliary model are implicitly a function of the parameters of the economic model, we obtain an indirect estimator by finding the parameter values that make the simulated data as similar as possible to the statistics we observe. Gourieroux et al. (1993) demonstrated that the indirect estimator is consistent and asymptotically normal by showing that the auxiliary statistics estimated from the data and the statistics generated through simulations from the structural model converge to the same pseudo-true value as the sample size increases.

In this paper, we use a mixture of likelihoods and moments to construct the auxiliary model. The likelihood portion of the auxiliary model was built around the framework used by Altonji et al. (2013) and Holmberg (2021) and consists of three components. Our auxiliary model was constructed to be similar to the structural model, as we wanted it to capture the dimensions of the data that the structural model explains. The auxiliary model is constructed to be rich in parameters and information in order to capture the contemporaneous and dynamic relationships between labor market outcomes.

The first likelihood is a linear regression of residual earnings. The explanatory variables of this model include years of education $edu_i$, an interaction between education and being younger than 30 $edu_i(age < 30)$, a Chebyshev polynomial of order 3 in potential experience $P(xp_{iy})$, employment duration $D^E_{iy}$, the mean output gap during the year $RU_{iy}$, and an error term assumed to be i.i.d and normally distributed ($\varepsilon_{iy}$). The dependent variable $earn_{iy}^{aux}$ refers to annual earnings observed in the ASTRID data, information which is gathered at an annual frequency and is the data equivalent of Equation (1). This linear model provides information for the structural parameters determining earnings formation.

$$\begin{gathered} earn_{iy}^{aux} = \beta_0 + \beta_1 edu_i + \beta_2 edu_i(age < 30) + P(xp_{iy})\beta_{xp}^{e,aux} \\ +\beta_6 D_{iy}^{E} + \beta_7 RU_{iy} + \varepsilon_{iy}. \end{gathered} \tag{9}$$

We use the residuals of this regression $\tilde{earn}_{it}$ and a measure of the variability of earnings $ln(1 + \tilde{earn}_{it}^2)$ based on this residual as dependent variables in the second and third components of the auxiliary likelihood. This process follows from Altonji et al. (2013) and the abovementioned variables help with the identification of parameters that affect the level and change in earnings variability over time; for example, the way earnings variability is affected by unemployment. The second and third components of the auxiliary likelihood are two sets of seemingly unrelated regression (SUR) models that share the same set of dependent variables but cover different parts of the data. The first SUR model covers the main elements of working life, while the second SUR model covers the initial observations in the data using a more restricted set of regressors. The set of common dependent variables $Y_{iy}$ is:

$$Y_{iy} = [E_{iy}^{E},\, U_{iy}^{E},\, \tilde{earn}_{iy},\, ln(1 + \tilde{earn}_{iy}^2)]. \tag{10}$$

The first two terms provide information on the transitions between unemployment and employment at an annual frequency. The regressors for the first SUR are:

$$\begin{gathered} X_{iy}^{s2} = \Big[1,\, xp_{iy},\, xp_{iy}^2,\, xp_{iy}^3, edu_i, edu_i(age_{iy} < 30) \\ RU_y,\, crisis_y,\, E_{i,y-1}^{E}, E_{i,y-2}^{E},\, U_{i,y-1}^{E},\, U_{i,y-2}^{E},\, D_{i,y-1}^{E},\, D_{i,y-1}^{U}, \\ earn_{i,y-1},\, earn_{i,y-2},\, earn_{i,y-3},\, earn_{i,y-1}xp_{iy}, earn_{i,t-1}xp_{iy}^2\Big], \\ if\; age > 28\; and\; calendar\; year > 2008. \end{gathered} \tag{11}$$

The auxiliary model should capture the dimensions of the data that our economic model aims to explain. From this perspective, it is natural to include the observable regressors of the economic model in the auxiliary model. The model also includes additional variables that capture other relevant aspects of the data. We include lagged terms of the first three dependent variables to facilitate a separate identification of time-invariant unobserved heterogeneity and state dependence. We use a three-year lag for earnings to help with identifying the autoregressive component of the productivity shocks. Interaction terms between earnings and potential experience are used to provide information on how the persistence of shocks changes with experience.

Since we use lagged variables as regressors, and since 2006 is the first year with both register and survey data, 2009 is therefore the first year that provides information for this SUR model. The use of lagged variables also means that the youngest workers observed in this part are 29 years old. We use a second SUR model with fewer lagged terms to provide information for the first years with data as well as the initial years on the labor market for the younger cohorts. This SUR does not include variables with lags longer than a year and was specified as follows:

$$\begin{gathered} X_{it}^{s3} = \Big[1,\ xp_{iy},\ xp_{iy}^2,\ xp_{iy}^3, edu_i, \\ edu_i(age_{iy} < 30),\ RU_y,\ D_{i,y-1}^U,\ D_{i,y-1}^E,\ crisis_y\Big], \\ if\ age \leq 28\ or\ calendar\ year \leq 2008. \end{gathered} \tag{12}$$

The three models for the likelihood part of the auxiliary model are estimated using different numbers of observations. We want these likelihoods to be comparable in size and for the weight assigned to them during the optimization to reflect the relative amounts of information they contain. For this reason, we normalize our sufficient statistics for the different likelihoods using the number of observations used in the first part as a reference. This means that the likelihood of the first part is weighted as being drawn from one observation, while the second and third likelihoods are given weights based on their sample size relative to the first part.[19] The likelihood functions can be found in Appendix A.

We use the proportion of the real and simulated LFS samples making a $E^E$ or $U^E$ transition each quarter to identify the within-year transitions into and out of employment. For

[19] Altonji et al. (2013) work around the problem of the likelihood functions having different scales numerically by assigning an arbitrary additional weight to the linear model which corresponds to the first likelihood in this paper. We believe that our approach provides a more transparent way of scaling the different likelihoods.

these statistics, we used the following moment conditions:

$$M = \sum_{q=1}^{40} \frac{(E_q^E - \hat{E}_q^E)^2}{\hat{\sigma}_E^2} + \frac{(U_q^E - \hat{U}_q^E)^2}{\hat{\sigma}_U^2}. \tag{13}$$

Where $E_q^E$ and $U_q^E$ represent the quarterly proportions observed in the data, while $\hat{E}_q^E$ and $\hat{U}_q^E$ are the same statistics using data simulated from the model. The moment conditions are scaled using the variance from the simulated moments. The variances of these proportions were calculated as if the sample size were 1 to match the normalization of the likelihood. The sum of all parts was then used as the objective for the optimization procedure. From the likelihoods, we obtain 144 parameters, including the unique elements of the variance-covariance matrices of the SURs, and we obtain 80 moment conditions from the quarterly transition rates. This exceeds the 34 parameters of the model, meaning our model is overidentified.

## 4.3 Initial conditions, starting values and smoothing

The simulation requires initial conditions and starting values. Individuals are assigned a year of birth and an education level based on the frequencies observed in the data. For men and women, we sampled the 1952–1990 cohorts and calculated proportions for all birth years and years of education combinations. Birth year and education level are then randomly assigned based on the observed probabilities.[20] Initial employment, employment duration, and unemployment duration are assigned based on probabilities conditioned on the year of birth and education level. The data includes information on the length of the current spell of employment.[21] As the simulations only cover the period 2006–2015, we can therefore use the observed probability of employment in 2005[22] to assign initial employment status. The mean difference between the RAMS and LFS employment levels over the period 2006–2015 is used to adjust for net classification error in 2005. As the RAMS data is annual, while the model operates at a quarterly level, it is necessary to balance these initial employment probabilities. Unemployment duration is not recorded in ASTRID. However, the data starts in 2002, which makes it possible to calculate an initial unemployment duration of up to four

[20]For example, 0.858 % of the women in the sample were born in 1976 and had 12 years of education. A simulated woman was therefore assigned that combination of birth year and education level with that probability.

[21]With a maximum of 18 years in 2002.

[22]As well as later years for the younger cohorts.

years for all cohorts.[23]

Since the estimation procedure is extremely computationally demanding, optimizing the model from different starting points is not feasible. Instead, we take most of the initial parameter values from the data. For the transition equations, we combine estimates from probit models fitted to the ASTRID data and regressions on log odds ratios from the LFS to obtain starting values for observable variables and seasonal effects. The intercepts of these equations were then adjusted to improve the initial fit to the data. We estimate a linear regression on residual earnings to get starting parameter values for the earnings process. Starting values for the productivity shocks were estimated by fitting an AR(1) model to the earnings residual from the linear regression using minimum distance estimation. These AR(1) parameters were then scaled to fit a quarterly frequency. For the unobserved heterogeneity, the earnings parameter was initiated at 0.1 and the others at 0. All starting values can be found in Appendix B.

# 5 Results

The estimates for the parameters related to the latent earnings are presented in Table 1, while the estimates related to the transition equations are presented in Table 2. We evaluate the fit of the model both using descriptive linear regressions and by comparing statistics from the data with statistics from simulations. Tables 3 and 4 show the results of the linear regressions, while Figures 2–4 compare simulated and observed statistics for men and women.

Table 1 shows the parameters that affect earnings formation. One of the most important questions in the earnings dynamics literature is concerned with the degree to which earnings shocks are persistent. We find this persistence to be relatively low with AR(1) parameters $\rho$, estimated to be 0.737 for men and 0.716 for women. These estimates are far from a unit root, especially considering that our model operated on a quarterly frequency. Gustavsson (2007), Gustavsson (2008) and Gustafsson and Holmberg (2019) found annual AR(1) parameters for annual earnings ranging between 0.344–0.652. Friedrich et al. (2019) found quarterly AR(1)

[23]We use this upper limit for initial unemployment duration for cohorts turning 24 after 2006 as well.

parameters of 0.962–0.971 among Swedish men, estimating an earnings dynamics model including labor market transitions and firm-level shocks. The model in this paper is better suited than traditional earnings dynamics models for dealing with unemployment spells, as it explicitly captures the transitions into and out of employment. This means that a smaller share of the estimated productivity shocks will be the result of unobserved variations in hours worked.

Education is important to consider when studying labor market outcomes. We find that the marginal effects of an additional year of education are equal to a 2.9 % increase in latent earnings for men and a 5.1 % increase for women. These estimated elasticities are in line with previous research of the returns on education in Sweden.[24] They are also consistent with the compressed wage structure in Sweden (Gottfries, 2018).

We now turn to the role of state dependence and unobserved heterogeneity. We find that these variables have relatively large contributions to observed earnings differences. The return in latent earnings of an additional year of continuous employment is 6.5 % for men and 5.5 % for women. These returns are estimated to be larger than those of education. Considering the returns on unobserved ability, we can use the fact that $\alpha_i$ is drawn from a standard normal distribution to interpret the parameter estimates. In this case, a coefficient of 0.306 for men and 0.385 for women implies that an individual belonging to the third quartile of the ability distribution can expect quarterly earnings that are 20.6 % and 26.0 % higher than those of workers in the middle of the distribution.

Finally, we evaluate the role of the business cycle in determining latent earnings $RU_{q-1}$. If the use of residual earnings is sufficient to control for the impact of common shocks, this coefficient should be 0. We find latent residual earnings to be slightly pro-cyclical for both men and women, and that the impact of the business cycle on earnings is small but not zero. This means that business cycle effects matter for earnings formation in earnings dynamics models with endogenous transitions.

[24] See for example Isacsson (1999), Bjorklund (2000) and Holmberg (2021).

| | Earnings Men | Earnings Women |
|---|---|---|
| $Constant$ | -1.254 | -1.286 |
| | (0.0003) | (0.0003) |
| $Education$ | 0.029 | 0.051 |
| | (0.0003) | (0.0002) |
| $xp$ | -0.508 | -0.542 |
| | (0.0002) | (0.0002) |
| $xp^2$ | -0.028 | 0.036 |
| | (0.0003) | (0.0002) |
| $xp^3$ | 0.155 | -0.047 |
| | (0.0003) | (0.0003) |
| $D_{it}^{E}$ | 0.065 | 0.055 |
| | (0.0003) | (0.0003) |
| $\theta_{\alpha}^{earn}$ | 0.306 | 0.385 |
| | (0.0004) | (0.0003) |
| $RU_{q-1}$ | 0.022 | 0.008 |
| | (0.0003) | (0.0003) |
| $\rho$ | 0.737 | 0.716 |
| | (0.0003) | (0.0003) |
| $\sigma^{earn}$ | 0.237 | 0.275 |
| | (0.0003) | (0.0003) |

Table 1: Parameter estimates for latent log earnings for men and women.
*Note: Standard errors are presented in parentheses beneath the estimates.*

Table 2 presents the parameter estimates regarding employment transitions. Two central questions asked in this study are how the business cycle affects labor market transitions and why we observe countercyclical unemployment rates on a macroeconomic level. The effect of the business cycle is captured by the output gap $RU_{q-1}$ and the crisis dummy. The positive coefficients for the output gap show that both the probability of remaining in employment and the probability of finding new employment are pro-cyclical. This suggests that one is more likely to find employment and less likely to become unemployed during times of economic expansion. We also find that the 2008/2009 financial crisis had a larger effect on job-finding rates than it did on the probability of remaining employed.

| | Men | | Women | |
|---|---|---|---|---|
| | $E^E$ | $U^E$ | $E^E$ | $U^E$ |
| $Constant$ | 1.402 | -1.814 | 1.391 | -1.843 |
| | (0.0002) | (0.0003) | (0.0003) | (0.0002) |
| $Education$ | 0.012 | 0.076 | 0.024 | 0.066 |
| | (0.0004) | (0.0003) | (0.0003) | (0.0003) |
| $Education_{20s}$ | -0.038 | 0.012 | -0.025 | -0.010 |
| | (0.0002) | (0.0003) | (0.0002) | (0.0002) |
| $xp$ | 0.051 | -0.407 | 0.558 | -0.354 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| $xp^2$ | -0.106 | 0.043 | -0.237 | -0.052 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| $D^E_{i,t-1}$ | 0.066 | - | 0.056 | - |
| | (0.0003) | | (0.0003) | |
| $D^U_{i,t-1}$ | - | -0.188 | - | -0.175 |
| | | (0.0003) | | (0.0003) |
| $\theta_\alpha$ | 0.331 | -0.377 | 0.260 | -0.752 |
| | (0.0002) | (0.0003) | (0.0003) | (0.0002) |
| $RU_{q-1}$ | 0.064 | 0.054 | 0.034 | 0.010 |
| | (0.0003) | (0.0003) | (0.0002) | (0.0003) |
| $Crisis$ | 0.071 | -0.207 | 0.062 | -0.141 |
| | (0.0004) | (0.0003) | (0.0003) | (0.0003) |
| $Q2$ | 0.424 | 0.262 | -0.016 | 0.373 |
| | (0.0002) | (0.0003) | (0.0003) | (0.0003) |
| $Q3$ | 0.086 | 0.416 | -0.236 | 0.505 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| $Q4$ | 0.066 | 0.144 | -0.243 | 0.216 |
| | (0.0003) | (0.0003) | (0.0002) | (0.0003) |

Table 2: Parameter estimates for transition equations for men and women.
*Note: Standard errors are presented in parentheses beneath the estimates.*

Turning to the effects education has on employment, we find that education has a greater effect on the probability of finding new employment than on the risk of becoming unemployed. This is in line with the findings of Weber (2002) and Riddell and Song (2011). We also find that the interaction between education and being younger than 30 has a negative effect on the probability of remaining in employment. This could be interpreted as a negative labor supply effect from individuals participating in higher education.

Analyzing the effects of unobserved ability and state dependence, we find that unobserved ability $\alpha_i$ has a positive effect on the probability of staying employed but a negative effect on the probability of finding employment. This could be an indication of higher reservation wages among more able workers or larger savings among high-income earners. Both would affect the expected duration of employment: the first by increasing the time it takes to find a suitable vacancy, and the second by reducing the incentive for searching for new employment. Finally, we find that the probability of remaining in both employment and unemployment increases the longer an individual stays in that state. We find that the estimates for $D^E_{i,t-1}$ are positive and that the estimates for $D^U_{i,t-1}$ are negative.

## 5.1 Model fit

The model fit has been evaluated using descriptive linear regressions by comparing observed and simulated statistics. The simulated statistics were estimated on data for 100,000 individuals over the 40 quarters between 2006–2015, generated from the model presented in Section 3 with the parameter estimates presented in Tables 1 and 2. Tables 3 and 4 provide a comparison of the simulated data as well as data from the ASTRID database using descriptive linear regressions. These regressions demonstrate how well the model manages to replicate the observed data in several important dimensions. This approach has previously been used in the literature by Altonji et al. (2013). Figure 2 provides a comparison of the statistics observed in the data with the simulated output for men, considering both yearly aggregates and life cycle statistics. The same graphs, using data for women, can be found in Figure 3. For these plots, the observed statistics were calculated from the ASTRID data. Transitions and employment rate by quarter for both women and men can be found in Figure 4. These predictions are compared with the flow and employment statistics found in the LFS. All statistics for transition rates are calculated conditional on the individual being in the relevant state.[25] These graphs provide a visual aid for comparing the output generated by the model and the statistics we observe; this approach has been used in previous literature (i.e., Low et al., 2010; Altonji et al., 2013; Card and Hyslop, 2021).

[25]I.e., the probability of leaving unemployment among those already unemployed and the probability of remaining in employment for the already employed.

Table 3 shows that the observed and simulated employment to employment transitions are very similar for male workers, with small variations in the estimated parameter values. From Table 4 we find similar results for women. The fit of the unemployment to employment transitions is similar for both genders, with only minor differences in the parameter estimates. There are, however, larger discrepancies in the parameter estimates for the earnings regressions. The differences between the estimates from the real and simulated data are relatively large regarding the estimated intercepts returns to education and employment duration. The models estimated on simulated data have smaller intercepts and larger returns to both education and employment duration. It is also worth noting that the parameter estimates found in Table 1 are more in line with the descriptive linear model fitted to the observed data than those from the linear model estimated using the simulated data.

| | $Earn \mid E_{it} = 1$ | | $E^E_{it} \mid E_{i,t-1} = 1$ | | $U^E_{it} \mid E_{i,t-1} = 0$ | |
|---|---|---|---|---|---|---|
| | Real | Sim. | Real | Sim. | Real | Sim. |
| $Constant$ | $-1.334$ | $-3.817$ | 0.897 | 0.851 | 0.258 | 0.279 |
| | (0.001) | (0.014) | (0.0003) | (0.002) | (0.002) | (0.007) |
| $Education$ | 0.059 | 0.090 | 0.001 | 0.001 | 0.013 | 0.018 |
| | (0.0001) | (0.001) | (0.00002) | (0.0001) | (0.0001) | (0.0005) |
| $Education_{20s}$ | | | $-0.002$ | $-0.005$ | $-0.001$ | $-0.005$ |
| | | | (0.00002) | (0.0001) | (0.0001) | (0.0004) |
| $xp$ | $-0.020$ | $-1.661$ | $-0.043$ | $-0.089$ | $-0.080$ | $-0.232$ |
| | (0.002) | (0.015) | (0.0002) | (0.001) | (0.001) | (0.005) |
| $xp^2$ | $-0.095$ | $-0.041$ | 0.003 | 0.026 | 0.012 | 0.111 |
| | (0.001) | (0.007) | (0.0002) | (0.001) | (0.001) | (0.004) |
| $xp^3$ | 0.094 | 0.375 | | | | |
| | (0.001) | (0.007) | | | | |
| $D^E_{i,t-1}$ | 0.039 | 0.220 | 0.005 | 0.008 | | |
| | (0.00003) | (0.0003) | (0.00001) | (0.00004) | | |
| $D^U_{i,t-1}$ | | | | | $-0.036$ | $-0.032$ |
| | | | | | (0.0001) | (0.0003) |
| $Crisis$ | 0.011 | 0.026 | $-0.007$ | $-0.002$ | $-0.051$ | $-0.076$ |
| | (0.001) | (0.005) | (0.0001) | (0.001) | (0.001) | (0.003) |
| Obs. | 15,347,620 | 738,004 | 15,666,685 | 736,661 | 2,732,395 | 142,212 |
| Adj. $R^2$ | 0.137 | 0.421 | 0.034 | 0.074 | 0.100 | 0.171 |
| Res. SE | 0.790 | 1.771 | 0.177 | 0.196 | 0.403 | 0.376 |

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 parentheses beneath estimated coefficients. Conditions for selection are based on rounded predictions for the simulated data.*

| | $Earn \mid E_{it} = 1$ | | $E_{it}^{E} \mid E_{i,t-1} = 1$ | | $U_{it}^{E} \mid E_{i,t-1} = 0$ | |
|---|---|---|---|---|---|---|
| | Real | Sim. | Real | Sim. | Real | Sim. |
| $Constant$ | −1.249 | −3.998 | 0.866 | 0.804 | 0.147 | 0.263 |
| | (0.002) | (0.017) | (0.0004) | (0.002) | (0.002) | (0.007) |
| $Education$ | 0.068 | 0.139 | 0.003 | 0.006 | 0.021 | 0.016 |
| | (0.0001) | (0.001) | (0.00003) | (0.0001) | (0.0001) | (0.0004) |
| $Education_{20s}$ | | | −0.001 | −0.005 | −0.002 | −0.004 |
| | | | (0.00002) | (0.0001) | (0.0001) | (0.0003) |
| $xp$ | −0.078 | −1.917 | 0.0004 | −0.019 | −0.085 | −0.043 |
| | (0.002) | (0.017) | (0.0002) | (0.001) | (0.001) | (0.004) |
| $xp^2$ | 0.060 | 0.201 | −0.005 | 0.0001 | 0.003 | 0.021 |
| | (0.001) | (0.008) | (0.0002) | (0.001) | (0.001) | (0.003) |
| $xp^3$ | −0.133 | −0.276 | | | | |
| | (0.001) | (0.009) | | | | |
| $D_{i,t-1}^{E}$ | 0.030 | 0.208 | 0.004 | 0.006 | | |
| | (0.00003) | (0.0003) | (0.00001) | (0.00004) | | |
| $D_{i,t-1}^{U}$ | | | | | −0.033 | −0.041 |
| | | | | | (0.0001) | (0.0003) |
| $Crisis$ | 0.009 | 0.089 | −0.005 | −0.005 | −0.042 | −0.065 |
| | (0.001) | (0.006) | (0.0001) | (0.001) | (0.001) | (0.002) |
| Obs. | 14,666,079 | 708,203 | 14,888,121 | 703,732 | 3,205,767 | 175,737 |
| Adj. $R^2$ | 0.109 | 0.406 | 0.028 | 0.069 | 0.115 | 0.141 |
| Res. SE | 0.892 | 1.981 | 0.194 | 0.210 | 0.402 | 0.378 |

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

Figure 2 shows that the model predicts most labor market outcomes for men fairly well, both over calendar years and over the lifecycle. The overall employment level and the accumulation of durations are well-predicted in both dimensions. The employment-to-employment and unemployment-to-employment transitions are accurately predicted over calendar years, while the fit over the lifecycle, particularly for the young workers, is not as good. One obvious reason for this finding is that the interaction term between education level and being younger than 30 is an imperfect instrument for capturing the labor supply effect of individuals studying. The prediction of earnings over calendar years and the lifecycle is not as good as the prediction of other labor market outcomes. The predictions from the model fluctuate around the observed statistics over the lifecycle, while tending to be higher than the observed earnings over calendar years. Recall that the demeaning of log earnings means that the observed statistics for average earnings for calendar years are 0 by construction.

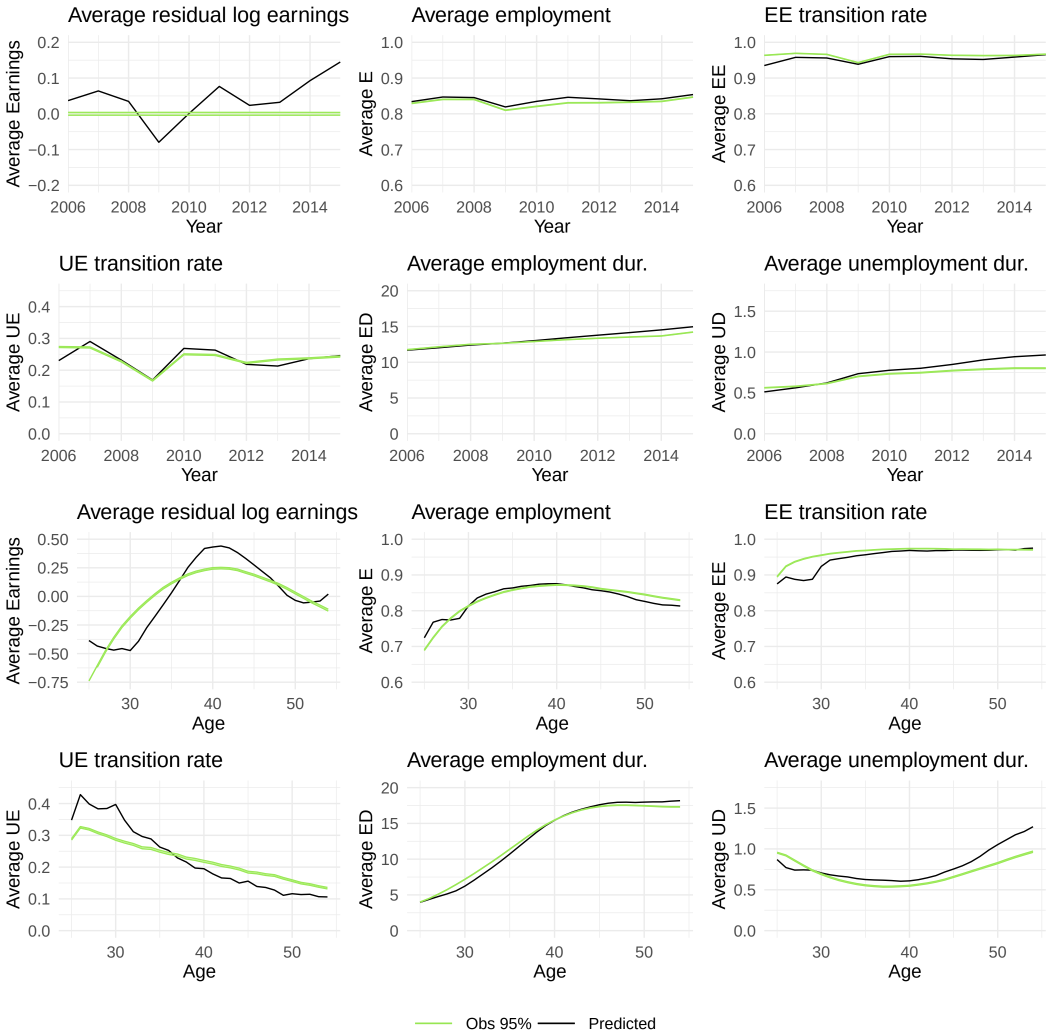


Figure 2: Predicted and observed outcomes over calendar years and the life cycle for men.
*Note: Observed statistics are presented as a 95% confidence interval around the mean.*

Figure 3 provides a comparison of observed and predicted labor market outcomes for women. The model manages to predict the outcomes over calendar years fairly well. Predicted earnings, $E^E$ transition rates and earnings are slightly below the observed statistics, while the average unemployment duration is a bit above the observed statistics. The fit over the lifecycle is good after the age of 35, but relatively poor during the first years in the labor market.

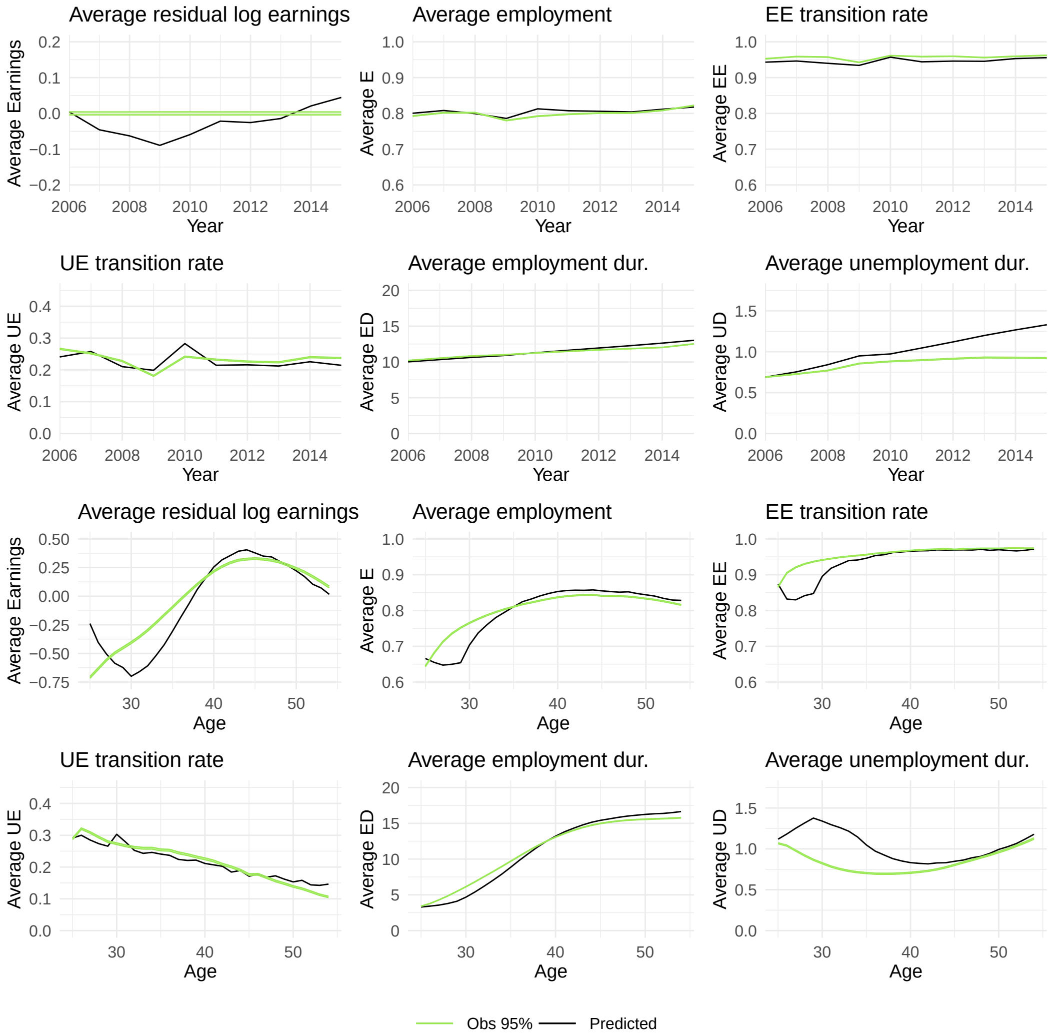


Figure 3: Predicted and observed outcomes over calendar years and the life cycle for female workers.
*Note: Observed statistics are presented as a 95% confidence interval around the mean.*

Figure 4 shows how the model fits the transition rates and employment levels at a quarterly level. These statistics are relatively well-predicted by the model. We see that the predicted employment level for men is higher than that of women, and that the $U^E$ transition rates are more volatile than the $E^E$ transitions. These plots show how the model fits 360 statistics for men and women. We would argue that the fit is relatively good given that the model only contains 34 parameters.


Figure 4: Transitions by quarter for all workers.

# 6 Model applications

This section provides examples of how the model can be used to study key labor market dynamics as well as the interactions between business cycle fluctuations and labor market outcomes. Section 6.1 provides an analysis of how the business cycle, unobserved ability, and productivity shocks affect the earnings distribution generated by the model. In Section 6.2, we use the model to study labor market outcomes with and without business cycle effects. Section 6.3 provides an analysis of how earnings and employment are affected by crises of different lengths. In Section 6.4, we present an analysis of the relationship between unemployment and real earnings growth. All statistics have been generated using the model presented in Section 4, and the reference or baseline scenario uses the parameter estimates found in Section 5. Counterfactual scenarios are generated by either altering some parameter values of the model or by changing the macroeconomic environment. Hereafter, we will refer to the parameters related to the output gap and the crisis as the business cycle.

## 6.1 Earnings inequality

Table 5 shows how different components of the model affect the distribution of earnings and contribute to earnings inequality. We compare the distribution earnings generated by the model with counterfactual scenarios in which different elements of the model have been removed. These simulations were performed using 2006 prices, and we examine the distribution of average annual log earnings over the period 2006–2015. We compare a baseline earnings distribution with the distributions generated by the model without business cycle effects (BC), without any unobserved ability $\alpha_i$, and without the productivity shocks AR(1).[26] From this table, we find that unobserved ability contributes the most to observed earnings inequality. Removing these parameters reduces the interquartile range and variance of the earnings distribution of both men and women the most. This is followed by the contributions made by idiosyncratic productivity shocks. In comparison, the business cycle makes a relatively small contribution to the observed earnings inequality. Mueller (2017), Krusell et al. (2020), and Gulyas and Pytka (2020) have found that a larger proportion of high-income earners and workers better attached to the labor market lose their jobs during recessions. We find that individuals with higher earnings are less prone to leaving unemployment. These types of mechanisms could work towards business cycle fluctuations, reducing life cycle earnings inequality.

| | Men | | | | Women | | | |
|---|---|---|---|---|---|---|---|---|
| | Base | BC | $\alpha_i$ | AR(1) | Base | BC | $\alpha_i$ | AR(1) |
| *1st Q.* | 3.956 | 3.995 | 4.539 | 4.218 | 2.569 | 2.604 | 3.516 | 2.832 |
| *Median* | 6.844 | 6.857 | 6.953 | 7.023 | 5.697 | 5.691 | 6.002 | 5.823 |
| *Mean* | 6.294 | 6.324 | 6.382 | 6.293 | 5.484 | 5.493 | 5.667 | 5.483 |
| *3rd Q.* | 8.833 | 8.859 | 8.634 | 8.678 | 8.254 | 8.251 | 8.070 | 8.129 |
| *Var.* | 11.508 | 11.440 | 9.241 | 9.951 | 12.901 | 12.832 | 9.904 | 11.250 |

Table 5: The distribution of real earnings as generated by the model (Base) and without the effect of the business cycle (BC), without unobserved heterogeneity ($\alpha_i$) and without productivity shocks (AR(1)) for men and women.

[26] The counterfactual scenarios are generated by setting the corresponding parameter values to 0 and simulating new data beginning from the same seeds as the baseline scenario.

## 6.2 Business cycles and labor market outcomes

Figure 5 shows labor market outcomes in terms of residual earnings, earnings volatility, and employment for men and women as predicted by the model. It also shows how these outcomes change when the effects of the business cycle are removed. From these graphs, we observe that men are affected more by business cycle fluctuations than women. Further calculations show that the standard deviation between the yearly outcomes with and without the business cycle effects is more than twice as large for men as it is for women. One explanation for this could be that women are, to a larger extent, employed in the public sector[27], which is less sensitive to business cycle fluctuations.[28] We can also see that the business cycle has a larger negative effect on employment levels among the relatively young.

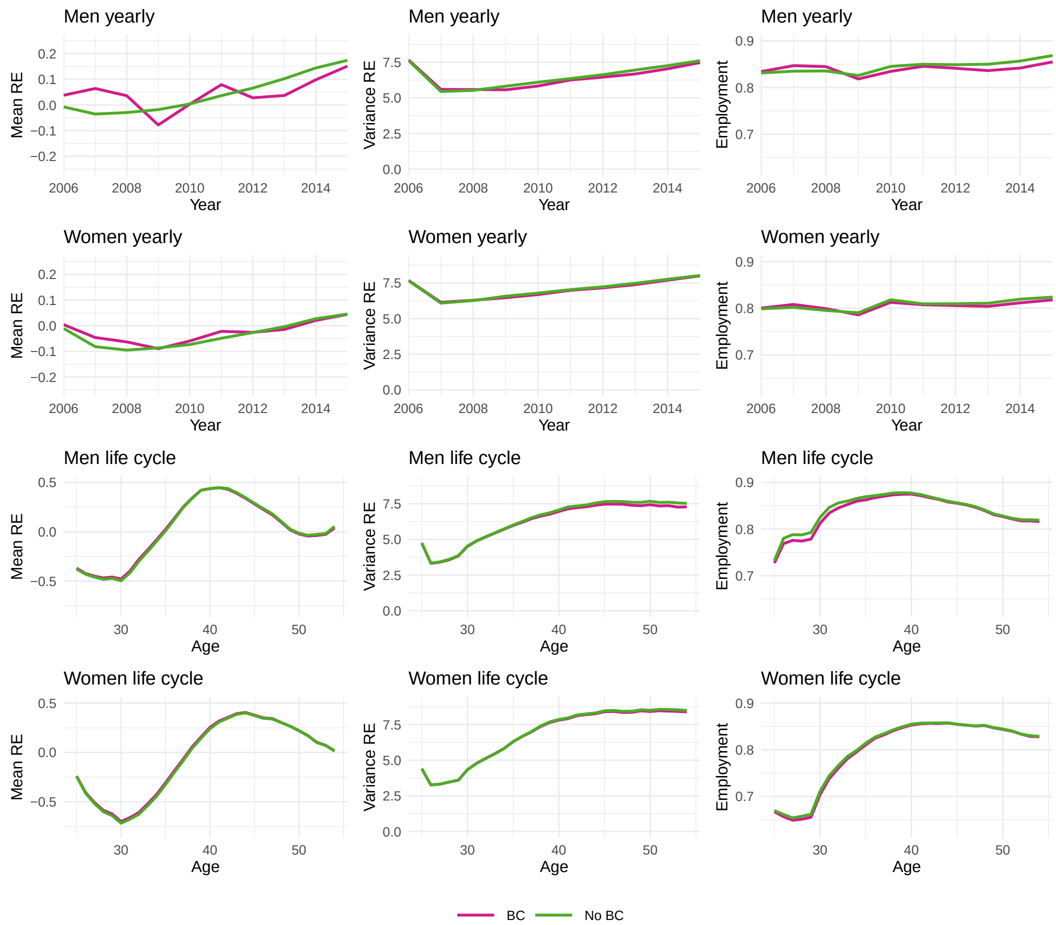


Figure 5: Labor market outcomes with and without business cycle effects.

[27]See Appendix C.

[28]Looking at U.S data Quadrini and Trigari (2007) found that employment and wages in the public sector are less procyclical than in the private sector.

## 6.3 Economic crises

The third application analyzes the effect economic crises of varying lengths have on earnings and employment, and how the adverse effects are distributed among different workers. The baseline scenario was generated by simulating the model, setting the output gap and crisis dummy to 0 for all periods. We repeat the simulations starting from the same seed, this time imposing a crisis state. The crisis state is defined as the output gap being set to the mean output gap for the period 2008–2009, and the crisis dummy is set to 1.[29] We test four different scenarios and compare their outcomes with the baseline case. All crisis states begin in the second quarter of 2006 and last for 2, 4, 8, or 12 quarters. We restrict the calculation of statistics such that they only contain individuals directly affected by the crisis. This means that only the cohorts born before 1982 are considered when calculating the statistics.[30] We also remove individuals with 8 years of education when calculating statistics by education group, as this group is too small to reliably calculate statistics.[31] Figure 6 shows how economic crises of various lengths affect the relative employment rates and earnings levels of all workers.

In this figure, we find that economic crises have a more persistent negative effect on earnings than they do on employment. This finding is in line with Davis and Von Wachter (2011) and Holmberg (2021), who found large and persistent negative effects from displacement on earnings. We also find that younger workers are affected by the crises more than older workers. Looking at the quarterly transition rates, we observe that the employment-to-employment transition probabilities are less sensitive to economic crises than the job-finding probabilities for the unemployed. This is consistent with the view that it is the fluctuation in search frictions that drive unemployment fluctuations over the business cycle.

[29] We performed the same simulations setting the output gap to the minimum level over the period 2008–2009 as well. The graphs produced under these conditions were visually indistinguishable from the ones presented in this paper.

[30] Depending on the length of the crisis, younger cohorts could enter the labor market after the crises have ended.

[31] The 8-year education was decommissioned from the Swedish educational system in 1972 and is uncommon in the data. In the simulated sample of 100,000 men and 100,000 women, only 10 individuals in total received this particular type of education.

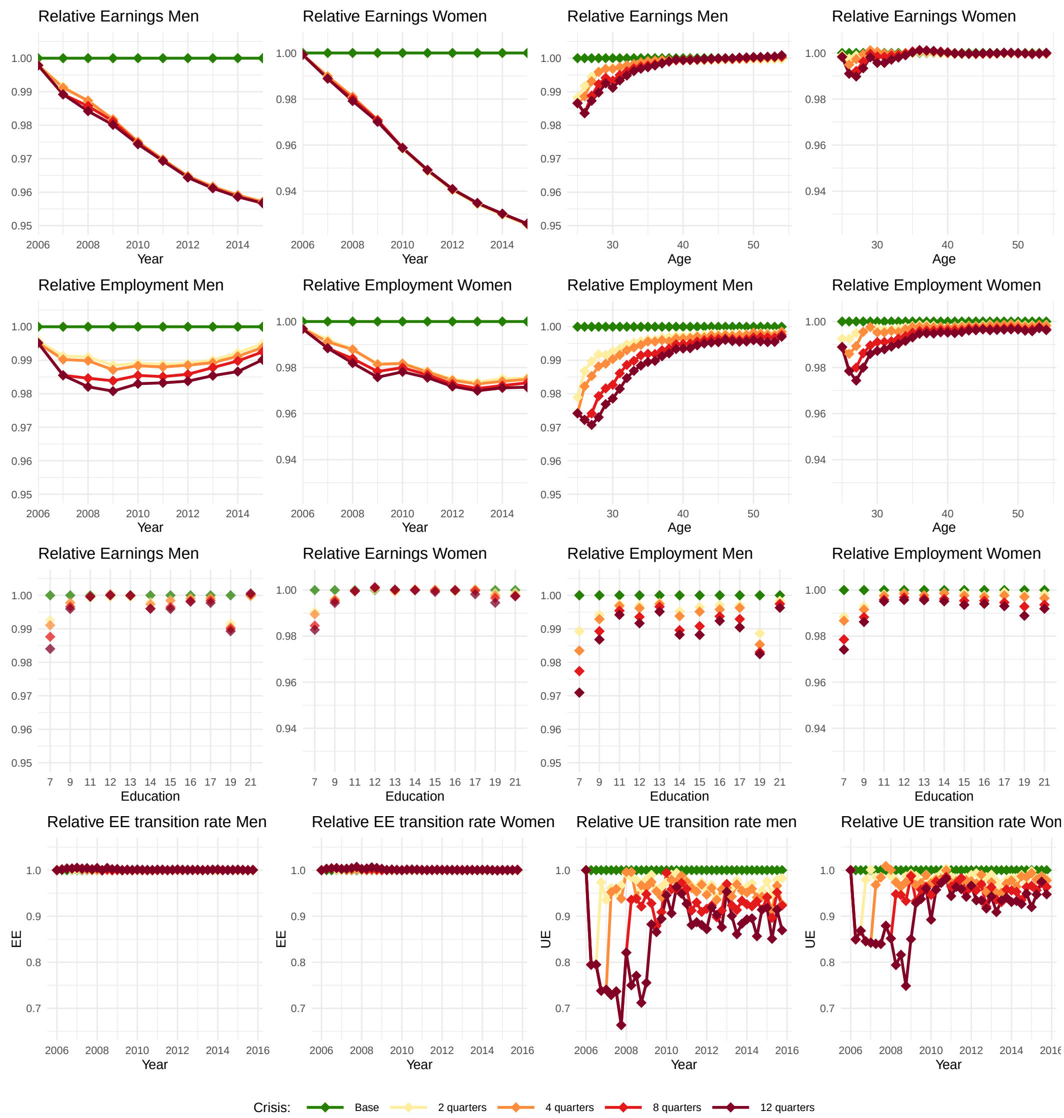


Figure 6: Relative earnings and employment levels with crises of varying length.

## 6.4 The Phillips curve

This section includes a simulation of the Phillips curve for the Swedish labor market from 2006–2015. The relationship between unemployment and inflation can help us determine much we should worry about inflation when designing and implementing stimulus policies, a question that is highly relevant during the current pandemic and will be equally important when dealing with future economic crises. The debate surrounding the Phillips curve, the relationship between domestic unemployment and (wage) inflation[32] proposed by Phillips

[32]Today it is more common to discuss the relationship between unemployment and consumer price inflation, even though Phillips (1958) studied the relationship between unemployment and wage inflation.

(1958), has intensified after the 2008/2009 financial crisis. Some have argued that this relationship has weakened since the 1990s (e.g., Blanchard et al., 2015) or become more dependent on global factors (e.g., Borio and Filardo, 2007; Auer et al., 2017). Estimating the slope of the Phillips curve using a novel method incorporating regional data Hazell et al. (2020) has found the Phillips curve to be very flat in the U.S., and indeed that it was flat during the 1980s as well. A flat Phillips curve implies a weak relationship between unemployment and inflation, which implies a low risk that an expansive stabilization policy would trigger high inflation levels. As a small, trade-dependent open economy, Sweden is an interesting case in this debate, as this economic landscape should weaken the link between domestic unemployment and inflation. Analyzing Swedish unemployment and inflation data Karlsson and Österholm (2019) did not find evidence supporting the view that the Swedish Phillips curve has been flatter in recent years.

Figure 7 shows the observed and simulated Phillips curve for men and women in Sweden. The observed Phillips curve uses information on quarterly employment rates and inflation measured using the consumer price index with fixed interest rates in Sweden from 2006–2015. This information was gathered from Statistics Sweden's public records. The simulated Phillips curve is based on simulations of 100,000 men and 100,000 women using the model. These figures show the relationship between the unemployment rate and the quarterly percentage change in average real earnings over the same period.

We find that although the observed relationship between unemployment and inflation is relatively weak, the correlation between unemployment and the rate of real earnings growth is stronger. This suggests that even if the Phillips curve appears flat, the risk of expansive fiscal or monetary policy fueling wage inflation continues to exist and should be considered when formulating stabilization policies. Even though the model does not explicitly include wage bargaining, we find a relatively strong relationship between unemployment and real earnings growth. Since we allow for unobserved heterogeneity, and as the model is fitted to the employment level at different times, the model captures changes in the composition of the employed workforce over the business cycle. This provides a possible explanation for the relationship between employment and earnings growth. Another mechanism could be state dependence: when unemployment is low, average employment duration is likely to increase. Since this affects earnings formation, we would expect earnings growth whenever unemployment levels are low.

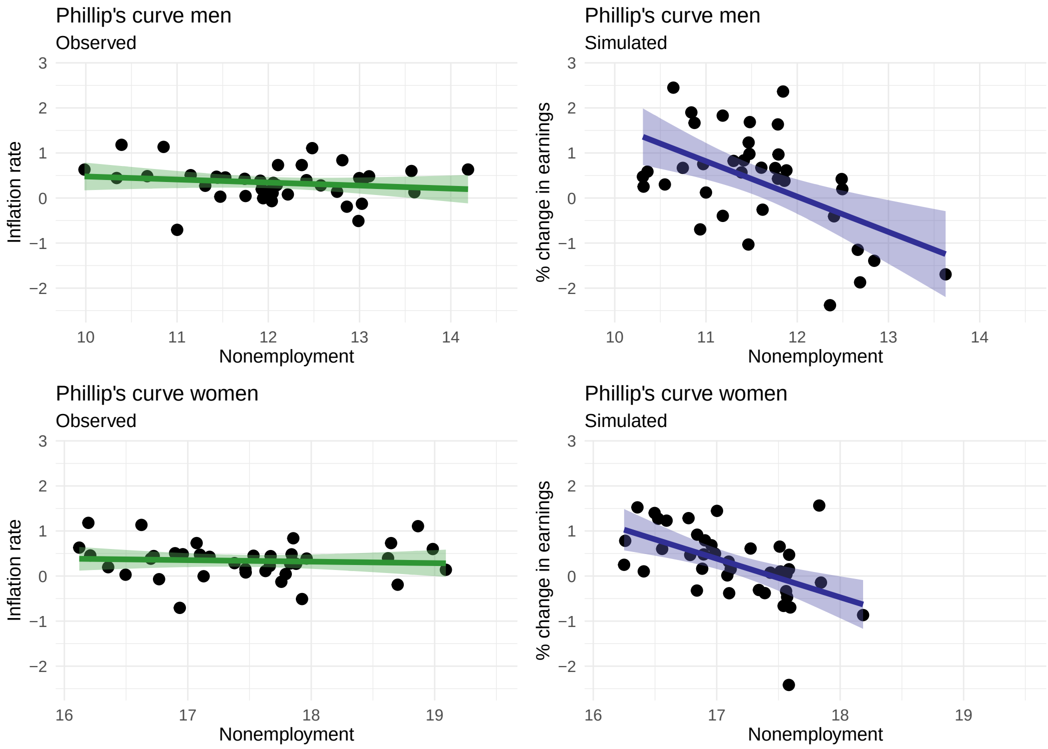


Figure 7: Observed relationship between non-employment and inflation by quarter in Sweden 2006–2015 and relationship between real earnings growth and non-employment as predicted for the same time period by the model.

# 7 Conclusions

In this paper, we construct and estimate a model of earnings and employment dynamics that includes business cycle fluctuations. We find that the business cycle affects the dynamic properties of earnings and that this effect should be taken into account when estimating earnings dynamics models, including labor market transitions. We find that men are slightly more affected by the business cycle than women. One explanation for this could be that different sectors, such as the private and public sectors, are affected differently by the business cycle. In Sweden, the shares of men and women working in the private sector differ substantially. The question of heterogeneity in business cycle effects between sectors is beyond the scope of this paper, but could be explored in future research. We also use the model to study how the business cycle affects earnings inequality and employment, and find that the contribution of the business cycle to earnings inequality is relatively small.

Our findings support the view that the main factor driving unemployment fluctuations over time is changes in the probability of the unemployed finding new employment, not fluctuations in the risk of employed individuals becoming unemployed. These findings suggest that policies aimed at reducing search frictions, such as labor intermediation services or retraining programs, may be more effective in reducing variations in unemployment over the business cycle than policies aimed at reducing separation rates, such as furlough schemes.

We study how economic crises of different lengths affect aggregate earnings and employment levels over time and for different groups. In this analysis, we find that younger workers are more sensitive to economic crises than individuals that are more established in the labor market. Short employment spells and labor market regulations restricting the order of layoffs likely contribute to young workers being sensitive to business cycle shocks in Sweden.

Finally, we analyze the relationship between unemployment and real earnings growth, and find that the earnings growth rate increases when unemployment decreases. This effect exists despite the fact that the relationship between the observed unemployment rate and inflation in Sweden was weak during the same period. These findings suggest that expansive fiscal or monetary policies could fuel wage inflation, meaning that we should consider the inflation risk when formulating stabilization policies.

# References


Ahn, H. J. and Hamilton, J. D. (2020). Heterogeneity and unemployment dynamics. *Journal of Business & Economic Statistics*, 38(3):554–569.

Altonji, J. G., Smith Jr, A. A., and Vidangos, I. (2013). Modeling earnings dynamics. *Econometrica*, 81(4):1395–1454.

Andolfatto, D. (1996). Business cycles and labor-market search. *The american economic review*, pages 112–132.

Arvidson, G., Bengtsson, T., Durnell, U., Ängsved Marianne, Flygare, A.-M., and Odencrants, M. (2005). Sysselsättningsavgränsningen: Metodöversyn i rams 2005. Technical report, Statistics Sweden.

Auer, R., Borio, C. E., and Filardo, A. J. (2017). The globalisation of inflation: the growing importance of global value chains.

Baker, M. and Solon, G. (2003). Earnings dynamics and inequality among canadian men, 1976–1992: Evidence from longitudinal income tax records. *Journal of Labor Economics*, 21(2):289–321.

Bangwayo-Skeete, P. F. and Skeete, R. W. (2015). Can google data improve the forecasting performance of tourist arrivals? mixed-data sampling approach. *Tourism Management*, 46:454–464.

Barsoum, F. and Stankiewicz, S. (2015). Forecasting gdp growth using mixed-frequency models with switching regimes. *International Journal of Forecasting*, 31(1):33–50.

Bessec, M. (2019). Revisiting the transitional dynamics of business cycle phases with mixed-frequency data. *Econometric Reviews*, 38(7):711–732.

Bjorklund, A. (2000). Education policy and returns to education. *Swedish Economic Policy Review*, 7(1):71–106.

Blanchard, O., Cerutti, E., and Summers, L. (2015). Inflation and activity–two explorations and their monetary policy implications. Technical report, National Bureau of Economic Research.

Blanchard, O. J. and Diamond, P. (1990). The cyclical behavior of the gross flows of us workers. *Brookings Papers on Economic Activity*, 1990(2):85–155.

Borio, C. E. and Filardo, A. J. (2007). Globalisation and inflation: New cross-country evidence on the global determinants of domestic inflation.

Bruins, M., Duffy, J. A., Keane, M. P., and Smith Jr, A. A. (2018). Generalized indirect inference for discrete choice models. *Journal of Econometrics*, 205(1):177–203.

Card, D. and Hyslop, D. R. (2021). Female earnings inequality: The changing role of family characteristics and its effect on the extensive and intensive margins. *Journal of Labor Economics*, 39(S1):S59–S106.

Christiano, L. J., Eichenbaum, M. S., and Trabandt, M. (2016). Unemployment and business cycles. *Econometrica*, 84(4):1523–1569.

Darby, M. R., Haltiwanger, J. C., and Plant, M. W. (1986). The ins and outs of unemployment: The ins win. Technical report, National Bureau of Economic Research.

Davis, S. J. and Von Wachter, T. M. (2011). Recessions and the cost of job loss. Technical report, National Bureau of Economic Research.

Elsby, M. W., Hobijn, B., and Şahin, A. (2015). On the importance of the participation margin for labor market fluctuations. *Journal of Monetary Economics*, 72:64–82.

Elsby, M. W., Michaels, R., and Solon, G. (2009). The ins and outs of cyclical unemployment. *American Economic Journal: Macroeconomics*, 1(1):84–110.

Friedrich, B., Laun, L., Meghir, C., and Pistaferri, L. (2019). Earnings dynamics and firm-level shocks. Technical report, National Bureau of Economic Research.

Fujita, S. (2011). Dynamics of worker flows and vacancies: evidence from the sign restriction approach. *Journal of Applied Econometrics*, 26(1):89–121.

Fujita, S. and Ramey, G. (2009). The cyclicality of separation and job finding rates. *International Economic Review*, 50(2):415–430.

Ghysels, E., Santa-Clara, P., and Valkanov, R. (2006). Predicting volatility: getting the most out of return data sampled at different frequencies. *Journal of Econometrics*, 131(1-2):59–95.

Ghysels, E., Sinko, A., and Valkanov, R. (2007). Midas regressions: Further results and new directions. *Econometric Reviews*, 26(1):53–90.

Gorry, A., Munro, D., and vom Lehn, C. (2020). Experience, skill composition, and the persistence of unemployment fluctuations. *Labour Economics*, 63:101793.

Gottfries, N. (2018). The labor market in sweden since the 1990s. *IZA World of Labor 2018*, 411 doi:10.15185/izawol.411.

Gourieroux, C., Monfort, A., and Renault, E. (1993). Indirect inference. *Journal of applied econometrics*, 8(S1):S85–S118.

Gulyas, A. and Pytka, K. (2020). Understanding the sources of earnings losses after job displacement: A machine-learning approach.

Gustafsson, J. and Holmberg, J. (2019). Earning dynamics in sweden: The recent evolution of permanent inequality and earnings volatility. *Umeå Economic Studies No. 963.*

Gustavsson, M. (2007). The 1990s rise in swedish earnings inequality–persistent or transitory? *Applied Economics*, 39(1):25–30.

Gustavsson, M. (2008). A new picture of swedish earnings inequality: Persistent and transitory components, 1960–1990. *Review of Income and Wealth*, 54(3):324–349.

Hall, R. E. (2005a). Employment fluctuations with equilibrium wage stickiness. *American economic review*, 95(1):50–65.

Hall, R. E. (2005b). Job loss, job finding, and unemployment in the us economy over the past fifty years. *NBER macroeconomics annual*, 20:101–137.

Hazell, J., Herreño, J., Nakamura, E., and Steinsson, J. (2020). The slope of the phillips curve: evidence from us states. Technical report, National Bureau of Economic Research.

Holmberg, J. (2021). Earnings and labor market dynamics: Indirect inference based on swedish register data. *Umeå Economic Studies No. 984.*

Humphries, J. E. (2017). The causes and consequences of self-employment over the life cycle. *Job Market Paper, University of Chicago.*

Häkkinen Skans, I. (2019). Labour market development according to different statistical sources. Sveriges Riksbank.

Isacsson, G. (1999). Estimates of the return to schooling in sweden from a large sample of twins. *Labour Economics*, 6(4):471–489.

Jovanovic, B. (2019). The entrepreneurship premium. *Small Business Economics*, 53(3):555–568.

Karlsson, S. and Österholm, P. (2019). A note on the stability of the swedish phillips curve. *Empirical Economics*, pages 1–40.

Kässi, O. (2014). Earnings dynamics of men and women in finland: permanent inequality versus earnings instability. *Empirical Economics*, 46(2):451–477.

Keane, M. and Smith, A. A. (2003). Generalized indirect inference for discrete choice models. *Yale University.*

Kihlstrom, R. E. and Laffont, J.-J. (1979). A general equilibrium entrepreneurial theory of firm formation based on risk aversion. *Journal of political economy*, 87(4):719–748.

Krusell, P., Mukoyama, T., Rogerson, R., and Şahin, A. (2020). Gross worker flows and fluctuations in the aggregate labor maarket. *Review of Economic Dynamics.*

Laussel, D. and Le Breton, M. (1995). A general equilibrium theory of firm formation based on individual unobservable skills. *European Economic Review*, 39(7):1303–1319.

Lillard, L. A. and Weiss, Y. (1979). Components of variation in panel earnings data: American scientists 1960-70. *Econometrica: Journal of the Econometric Society*, pages 437–454.

Lillard, L. A. and Willis, R. J. (1978). Dynamic aspects of earning mobility. *Econometrica: Journal of the Econometric Society*, pages 985–1012.

Low, H., Meghir, C., and Pistaferri, L. (2010). Wage risk and employment risk over the life cycle. *American Economic Review*, 100(4):1432–67.

MaCurdy, T. E. (1982). The use of time series processes to model the error structure of earnings in a longitudinal data analysis. *Journal of econometrics*, 18(1):83–114.

McFadden, D. (1989). A method of simulated moments for estimation of discrete response models without numerical integration. *Econometrica: Journal of the Econometric Society*, pages 995–1026.

Merz, M. (1995). Search in the labor market and the real business cycle. *Journal of monetary Economics*, 36(2):269–300.

Moffitt, R. A. and Gottschalk, P. (1995). *Trends in the Autocovariance Structure of Earnings in the US, 1969-1987.* Johns Hopkins University, Department of Economics.

Mortensen, D. T. (1970). Job search, the duration of unemployment, and the phillips curve. *The American Economic Review*, pages 847–862.

Mortensen, D. T. and Pissarides, C. A. (1994). Job creation and job destruction in the theory of unemployment. *The review of economic studies*, 61(3):397–415.

Mueller, A. I. (2017). Separations, sorting, and cyclical unemployment. *American Economic Review*, 107(7):2081–2107.

Nyman, C. (2010). An indicator of resource utilisation. Technical report, Sveriges Riksbank.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the united kingdom, 1861-1957. *economica*, 25(100):283–299.

Pissarides, C. A. (1985). Short-run equilibrium dynamics of unemployment, vacancies, and real wages. *The American Economic Review*, 75(4):676–690.

Quadrini, V. and Trigari, A. (2007). Public employment and the business cycle. *Scandinavian Journal of Economics*, 109(4):723–742.

Riddell, W. C. and Song, X. (2011). The impact of education on unemployment incidence and re-employment success: Evidence from the us labour market. *Labour Economics*, 18(4):453–463.

Rissman, E. (2003). Self-employment as an alternative to unemployment.

Scarpetta, S., Pearson, M., Hijzen, A., and Salvatori, A. (2020). Job retention schemes during the covid-19 lockdown and beyond.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American economic review*, 95(1):25–49.

Shimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics*, 15(2):127–148.

Simmons, M. (2020). Job-to-job transitions, job finding and the ins of unemployment.

Smith, A. A. (1990). *Three essays on the solution and estimation of dynamic macroeconomic models*. PhD thesis, Duke University.

Smith, A. A. (1993). Estimating nonlinear time-series models using simulated vector autoregressions. *Journal of Applied Econometrics*, 8(S1):S63–S84.

Stjernström, O. (2011). Databasen astrid och befolkningsgeografi: exemplen integration och branfamiljernas geografi. *Geografiska Notiser*, 69(2):79–86.

Varadhan, R. and Gilbert, P. (2009). Bb: An r package for solving a large system of nonlinear equations and for optimizing a high-dimensional nonlinear objective function. *Journal of statistical software*, 32(1):1–26.

Weber, B. A. (2002). The link between unemployment and returns to education: evidence from 14 european countries. *Education+ Training*.

Yashiv, E. (2007a). Labor search and matching in macroeconomics. *European Economic Review*, 51(8):1859–1895.

Yashiv, E. (2007b). Us labor market dynamics revisited. *Scandinavian journal of Economics*, 109(4):779–806.

# Appendix A: Likelihood functions for the Auxiliary model

Let $\beta^{earn}$ represent the vector of coefficients and $X_{it}^{earn}$ represent the matrix of regressors, then the first component of the auxiliary log likelihood assumes the following form:

$$\begin{aligned}\mathcal{L}_1(E_{it}earn_{it}|X_{it}^{earn}, \beta^{earn}) = -\frac{N}{2}\big(ln(2\pi) + ln(\sigma_\varepsilon)\big)\\ -\frac{(earn_{it} - X_{it}\beta^{earn})'(earn_{it} - X_{it}\beta^{earn})}{2\sigma_\varepsilon^2}\end{aligned} \tag{A.1}$$

We can write the SUR models as follows:

$$Y_{iy} = B^s X_{iy}^s + e_{iy},\ e_{iy},\ iid \sim N(0, \Omega). \tag{A.2}$$

Let $(\Omega^s)$ represent the covariance matrix for the system of equations. As all equations in both of the SURs shares the same set of exogenous variables, one can write their likelihood functions as follows:

$$\begin{aligned}\mathcal{L}_s(Y|X^s,\ B^s,\ \Omega^s) = -\frac{1}{2}\Big[ln\big(|2\pi\Omega^s \otimes I_N|\big)\\ +\big(vec(Y) - X_D^s vec(B^s)\big)'(\Omega^s \otimes I_N)^{-1}\big(vec(Y) - X_D^s vec(B^s)\big)\Big],\ s\ =\ s2,\ s3\end{aligned} \tag{A.3}$$

# Appendix B: Starting values for parameters

| | Men | Women |
|---|---|---|
| $Constant$ | -1.000 | -1.000 |
| $Education$ | 0.059 | 0.071 |
| $Education_{20s}$ | 0.003 | 0.004 |
| $xp$ | 0.080 | 0.032 |
| $xp^2$ | -0.151 | 0.004 |
| $xp^3$ | 0.131 | -0.092 |
| $D_{it}^E$ | 0.038 | 0.030 |
| $\theta_\alpha^{earn}$ | 0.100 | 0.100 |
| $RU_{q-1}$ | 0.000 | 0.000 |
| $\rho$ | 0.942 | 0.926 |
| $\sigma^{earn}$ | 0.149 | 0.199 |

Table 6: Starting parameters for latent log earnings for men and women.
*Note: The objective function was not fully optimized when retrieving the parameter estimates.*

| | Men | | Women | |
|---|---|---|---|---|
| | $E^E$ | $U^E$ | $E^E$ | $U^E$ |
| $Constant$ | 1.400 | -1.800 | 1.400 | -1.800 |
| $Education$ | 0.029 | 0.046 | 0.052 | 0.076 |
| $Education_{20s}$ | -0.015 | -0.001 | -0.005 | -0.001 |
| $xp$ | -0.315 | -0.272 | 0.378 | -0.264 |
| $xp^2$ | -0.062 | -0.041 | -0.111 | -0.146 |
| $D^E_{i,t-1}$ | 0.060 | - | 0.050 | - |
| $D^U_{i,t-1}$ | - | -0.163 | - | -0.150 |
| $\theta_\alpha$ | 0.000 | 0.000 | 0.000 | 0.000 |
| $RU_{q-1}$ | 0.076 | 0.051 | 0.019 | 0.044 |
| $Crisis$ | -0.054 | -0.158 | -0.105 | -0.077 |
| $Q2$ | 0.380 | 0.409 | 0.298 | 0.263 |
| $Q3$ | 0.142 | 0.412 | -0.130 | 0.320 |
| $Q4$ | -0.039 | 0.133 | -0.153 | 0.121 |

Table 7: Starting parameters for transition equations for men and women.
*Note: The objective function was not fully optimized when retrieving the parameter estimates.*

# Appendix C: Employment by sector in Sweden 2006–2015

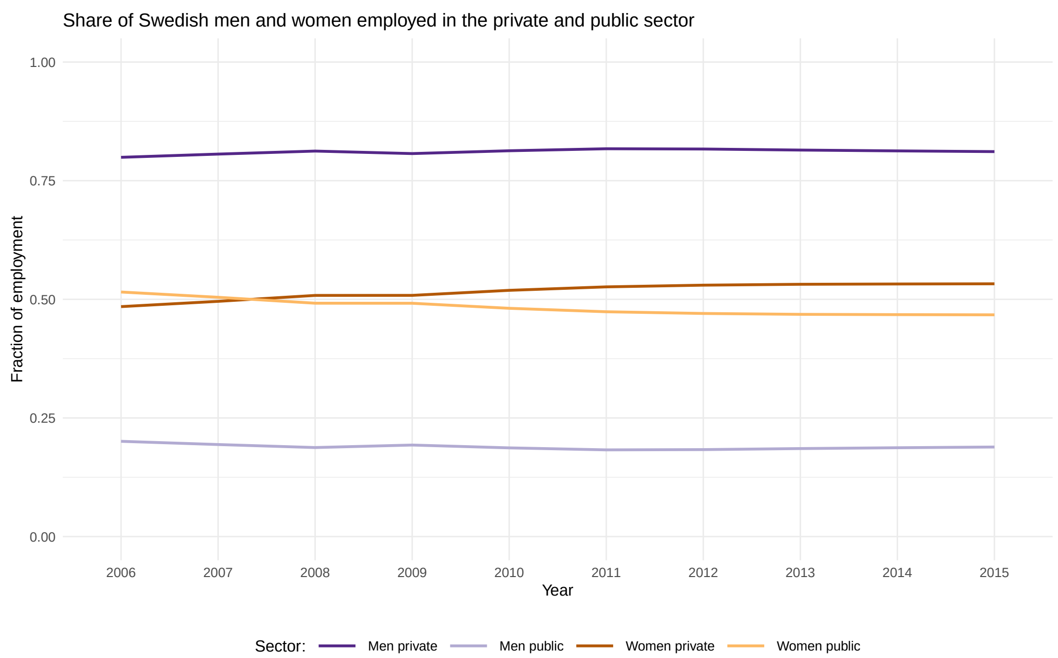


Figure 8: Proportion of men and women employed in the public and private sector over the years 2006–2015. Data was taken from Statistics Sweden.