On Returns to Effective Experience *

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Abstract

In this paper we study the process of human capital accumulation on the job. This has important implications for life-cycle inequality and cross-country differences in earnings. Using a novel dataset from Chile we document a significant gap in wage growth measured using job ad information versus the one observed in surveys of workers. We develop a lifecycle structural model where workers face frictional labour markets, uncertainty with respect to match quality with firms and uncertainty about human capital accumulation on the job. We quantify how much of the gap in job ad wage growth vs workers' survey wage growth is due to job market frictions (time not working) versus learning frictions. We find that failure to learn is the main reason behind the gap.

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1 Introduction

Heterogeneous wage growth over the lifecycle is closely linked to overall earnings inequality.[1] New evidence shows great disparity across countries (Lagakos et al. (2018) and Engbom (2019)).[2] The literature has provided two possible explanations for these facts: (i) labour market frictions, and (ii) heterogeneity in the human capital accumulation process.[3] In this paper, we study lifecycle wages and the process of general human capital accumulation through on-the-job learning. We analyze a novel dataset from a Chilean internet job board, where we observe a sizeable number of job advertisements, and more importantly, information on expected wages to be paid in each position along with a number of observable characteristics such as offered contracts and required education and experience. The data merge information on applicants, firms, applications, and job ads in a context of heterogeneous workers and positions where required experience is an observable job ad characteristic. To the best of our knowledge, this is a unique feature among databases of this sort that allows us to estimate returns to experience.

As a first contribution, we estimate profiles of log wages over different levels of *required* experience (in years) as measured in job advertisements controling for all possible observables, such as timing of the job posting and fixed effects at the firm and job title levels. We view these profiles as being closer to the true *returns to experience*. This is because the information provided by firms on expected wages to be paid at the advertised position does not depend on any particular worker, who may affect observed (ex-post) wages by way of different mechanisms: wage bargaining, individual match-quality or returns to (unobserved) worker skill, among others.

We further compare our estimated returns to experience (from job advertisement data) with lifecycle wages computed from the worker side. We estimate worker profiles using standard representative surveys of Chilean workers.[4] The comparison shows that returns to experience from job ads grow faster than observed lifecycle wages from workers.

We take the apparent mismatch found in the data as evidence of a failure to accumulate general human capital while working (on-the-job learning). Put it differently, if wage growth through job ads is two times larger than workers wage growth after 8 years, it must be that workers fail to

[1]Economic research on determinants of wage differentials go back to Mincer (1974). Since then, a large literature emerged on lifecycle wage growth and inequality (Deaton and Paxson (1994) and Storesletten et al. (2004), for example).

[2]For further cross-country cross-sectional comparison studies, see Dabla-Norris et al. (2015) and Tomaskovic-Devey et al. (2020).

[3]Frictional labour markets build from the work of McCall (1970), Mortensen (1970), Lucas and Prescott (1974), Burdett (1978), Pissarides (1985), Mortensen and Pissarides (1994), Burdett and Mortensen (1998), Hornstein et al. (2007) and Low et al. (2010). For recent applications, see Jung and Kuhn (2016), Engbom (2019). For cross-country differences in human capital see Bils and Klenow (2000), Caselli (2005) and Manuelli and Seshadri (2014). Economists have studied the relationship between human capital accumulation and inequality in Becker (1964), Ben-Porath (1967), Lucas (1988), Keane and Wolpin (1997) and Huggett et al. (2011). Examples of papers combining human capital accumulation and job search are Bowlus and Liu (2013) and Bagger et al. (2014).

[4]We also estimate worker's lifecycle wages using information from job seekers using the job board: both of these approaches give us almost identical results.

accumulate the demanded level of human capital requested by firms. To rationalize the facts, we put forward a structural labor supply model of the lifecycle, with two types of frictions: standard labor market ones and frictions on the actual process of human capital accumulation. The latter is represented as a simple extension of a Ben-Porath style model, where human capital accumulation is not deterministic but subject to some randomness. Our model also allows for a worker-firm idiosyncratic job match quality so that workers randomly differ in the fit with their corresponding firm.

While simple enough, our model fits Chilean data moments well and serves as a benchmark to start thinking about the failure of human capital accumulation. In the estimation, lifecycle effects are important, especially late in life. The probability of human capital depreciation through unemployment or job-to-job is estimated to be increasing over the lifecycle, while learning on the job (namely, the probability to increase human capital while working) is concave over the lifecycle, closely tracking workers' lifecycle wages.[5]

We use our model to quantify the role that each friction has in the observed wage mismatch. Our simulation exercises show that losing human capital through either unemployment or job-to-job have a lower impact on wage profiles than increasing one's human capital through on-the-job learning. This is in part because a worker spends most of his time at work, hence learning and increasing human capital while working is more relevant. In addition, we eliminate labour market frictions in order to measure their effect to close the gap in wage and job ads growth. Labour market frictions are less important quantitatively than failure-to-learn in explaining the returns gap. Eliminating job separation completely from our model can only close half the gap between worker vs. ads wage growth, while higher on-the-job learning can close the gap fully.

In this vein, we perform a counterfactual exercise where we choose the level of on-the-job learning so that we close the gap in wage and job ads growth. In this counterfactual, the level of on-the-job learning and the level of human capital accumulation are both four times above our baseline estimation. This exercise illustrates that failure-to-learn could be an important factor behind the gap between workers and firms wage growth. A non trivial implication of lower accumulation of human capital throughout the lifecycle is not only that Chilean average wages are lower, but also that inequality of earnings is larger, which should matter for welfare.[6] Although our model does not target Chilean labour earnings inequality measures, the results suggest that failure to accumulate human capital for a large fraction of workers throughout the lifecycle produces larger earnings inequality than in the counterfactual where wage and firms growth equal through higher accumulation of workers' human capital.

During the paper, we interchangeably use the terms "lifecycle wages", "worker side" and "supply

[5]It has to be said that although job-to-job creates some depreciation of human capital that increases over the lifecycle, workers still gain from switching jobs as they have incentives to find a good worker-firm job quality match throughout the lifecycle.

[6]Attanasio and Davis (1996).

side" to refer to workers' lifecycle wage profiles. We use the terms "ads wages", "job ads wages", "firm side" and "demand side" to refer to firms' job ads wage profiles by required experience. The rest of the paper is organized as follows. Section 2 describes the data sets, the facts, and the empirical findings. Section 3 presents the structural model. Section 4 discusses the parameter estimates and model fit. Finally, Section 5 uses the model to perform simulation exercises and a counterfactual by closing the worker vs. the ads wage growth mismatch.

2 The Facts

Data Source.

The main novel facts in this paper are related to the monthly wage profiles estimated using job posting information. This information can be thought of as direct evidence of *demand side* technological requirements in terms of experience profiles.

We use data from www.trabajando.com. Our data covers a sample of job postings and job seekers in the Chilean labor market between January 1st 2008 and December 24th, 2016. The raw information in the dataset contains more than 14 million single applications, from around 1.5 million job seekers, to around 270 thousand job ads.[7] In terms of the website's platform, job seekers can use the site for free, while firms are charged for posting ads. Job advertisements are posted for a minimum of 60 days, but firms can pay additional fees to extend this term.

For job seekers, we observe date of birth, gender,[8] nationality, place of residency ("comuna" and "región", akin to county and US state, respectively), marital status, self-reported years of experience, years of education,[9] college major and name of the granting institution of the major.[10] We have codes for occupational area of the current/last job of individuals,[11] information on their salary and both their starting and ending dates.

For each posting, we observe its required level of experience (in years), required college major (if applicable), indicators on required skills (specific, computing knowledge and/or "other") how many positions must be filled, the same occupational code applied to workers, geographic information ("región" only) and some limited information on the firm offering the job: its size (number of employees in brackets) and industry (1 digit code).

Besides this information, recruiters are also asked to record the expected pay for the job posting, and are given the choice whether to make this information visible or not to applicants. Naturally, one could question the reliability of wage information which will be ultimately hidden from the other side of the market. Banfi and Villena-Roldán (2019) address the potential issue of "nonsensical"

[7]A complete description of the website and the data is in Banfi and Villena-Roldán (2019).

[8]If we consider a sample of males alone (as in Lagakos et al. (2018), results are similar.

[9]Educational categories are *primary* (one to eight years of schooling), *high school* (completed high school diploma, 12 years), *technical tertiary education* (professional training after high school, usually 2-4 years), *college* (completed university degree, usually 5-6 years) and *post-graduate* (any schooling higher than college degree).

[10]This information is for any individual with some post high school education.

[11]We observe a one-digit classification, created by the website administrators.

wage information in job ads by comparing the sample of explicit vs. implicit (job ads without any salary information) postings by firms, and find that observable characteristics predict fairly well implicit wages and vice versa. Moreover, even if employers choose to hide wage offers, they are used in filters of the website for applicant search. Hence, employers are likely to report accurately even if their wage offers are not shown because misreporting may generate adverse consequences. Relatedly, Choi et al. (2020) show that wages in the website (both the explicit and hidden ones) are representative to the rest of the Chilean economy when compared to representative surveys of Chilean workers.

On the other hand, a major caveat of our dataset is the absence of information on activities performed outside the website: individuals seeking for jobs through other means, and more importantly, outcomes of job applications. However, for the purpose of our current exercise, this is not a major drawback since we are interested actually in the independent information contained in the website concerning expected salaries to be paid at different job positions and required experience. The main advantage of this wage data is that it is not contaminated by ex-post compensation nor specific worker skills at the individual level.

In the following exercise we impose minimal sample restrictions on the information from the website: we include all information on job advertisements and job seekers, as long as they have non-missing information on the observable characteristics for which we control. We ignore job advertisements that offer less than 100 thousand CLP,[12] or more than 5 million CLP per month (significantly above the 99-th percentile of the worker's salary distribution according to the CASEN survey, a representative survey of Chilean workers.)

Estimates of return to experience (Ads). Using the information on job ads only, we can compute the gradient of wages on *years of required experience*, which is information contained in all job ads on the website. Table 1 shows information of the job ads we use in our exercise. Our sample consists of more than 190 thousand individual job ads. In the table we show expected wages to be paid at the position, required experience, required education (only completed high school and college categories) and the main "area of job" categories.

In order to identify wage increases due to experience only, we run linear regressions on log-wages paid at each job ad, controlling for dummy variables for years of required experience and also controlling for a number of observable characteristics: year when the job ad was posted, required education, the area of the job, geographic location and industry of the firm and type of contract (full/part time). We further control for firm's identifier and job title fixed effects. The latter is constructed as in Banfi and Villena-Roldán (2019).[13]

Estimates of life-cycle wages (workers). For life-cycle wages (gradient of salaries with respect

[12] This is around 50% less than the minimum wage during 2008, which was set at 151,500 CLP per month.

[13] We identify the first four words of the job title variable and construct four categorical variables representing a list of words repeated more than 100 times in the whole sample of titles.

Table 1: Characteristics of Job Postings

	Average	Std.Dev.
Wage (thousand CLP)	620.70	533.71
Required experience (years)	1.94	1.80
Required education: High School	0.23	0.42
Required education: College	0.31	0.46
Area of job: Business-Management	0.27	0.44
Area of job: Technology	0.16	0.37
Area of job: Not specified	0.42	0.49
Number of obs.	190,280	

to workers' experience), we use the information provided by workers in the website. Table 2 shows summary statistics of workers. Compared to the CASEN survey, the sample of workers in the website is younger, more educated and more likely to be male and single than in the entire population of workers.

In Table 2 we show monthly salaries at the last job (self-reported by individuals) versus their current salary expectations: the expectations are around 5% higher than their current/last salary, which indicates that the website is used by and large individuals seeking to climb the wage ladder. This is also reflected in the fact that a sizeable number of individuals are currently employed when they use the website for job search (around 30%).

On the hand, we show two indicators of overall experience of workers: a standard calculation of potential experience,[14] and a self-reported experience. This latter number is lower and less disperse than the calculation of potential experience.

To compute the experience profile on the worker (supply) side, we use self-reported information on salaries at their last job and the self reported years of experience. More specifically, we run regressions with log-wages as dependent variables, on dummies for years of self-reported experience along a number of controls for observable characteristics: year of birth, year when the individual entered the website (creation of online profile), education level, gender, nationality, civil status, geographic area of residence, job area,[15] and employment status.

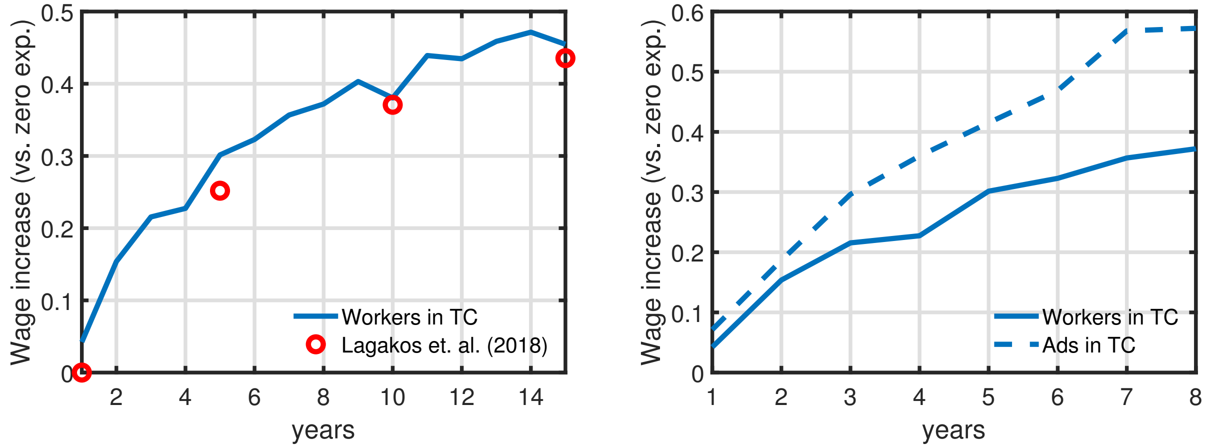
Empirical Results. From both the job ad and worker sides, we collect the OLS coefficients on years of required experience and self-reported experience respectively as our main estimates of experience profiles from the two sides of the market. This is displayed on the right panel of Figure

[14] This is computed as age minus 18 if total education of the worker is equal or less than 12 years; It is age minus 24 (18+6) otherwise.

[15] Self reported.

Table 2: Characteristics of Job Seekers

	Average	Std.Dev.
Wage expectations (thousand CLP)	729.00	641.71
Wage at last job (thousand CLP)	697.33	632.98
Potential experience (years)	9.49	8.99
Self-reported experience (years)	6.90	6.71
Age	32.63	8.92
Male	0.55	0.50
Single	0.69	0.46
High School	0.14	0.35
College	0.41	0.49
Area of worker: Business-Management	0.17	0.37
Area of worker: Technology	0.24	0.42
Area of worker: Not specified	0.38	0.49
Employed	0.30	0.46
Unemployed	0.44	0.50
Number of obs.	$1,037,493$	



Notes: The left panel displays workers' average wage increase throughout the first 15 years of their lifecycle. The solid line displays the raw data from www.trabajando.com (TC), while red dots display 5-year data intervals from Lagakos et al. (2018). The right panel displays workers' average wage increase throughout the first 8 years of their lifecycle (solid line) and average ads' posted wages by required experience from TC data (dashed line), net of firms and job title fixed effects.

Figure 1: Worker Side (Supply) vs. Ads Side (Demand)

1. The estimates in that panel are restricted by sample sizes of job ads with different experience requirements, thus we show estimates for only 8 years of experience. The main takeaway from this figure is the significant gap between the returns to experience at the job ad vs. the worker side.

On the left panel of the figure, we show the coefficients related to the first 15 years of self-reported experience using the equation for workers. Because the variables on required experience and self-reported experience may convey different information, we perform a robustness exercise where we compare our estimates with the estimates for the Chilean economy found in Lagakos et al. (2018). Even though it is estimated using a different data set and a different variable for experience (potential instead of self-reported), the figure shows that the estimates are remarkably close.

In the quantitative exercise below, we extrapolate the experience profile of the demand side (job ads). To obtain an estimate of this profile for years 9 onwards, we forecast using the annual life-cycle growth of worker wages implied in the estimates from Lagakos et al. (2018).

3 The Model

We develop a lifecycle, labour supply model based on Ben-Porath (1967), Keane and Wolpin (1997), Eckstein and Wolpin (1999) and Huggett et al. (2011) classic models of investment in human capital. Workers face: (i) frictional labour markets, (ii) uncertainty with respect to match quality with firms, and (iii) uncertainty about human capital accumulation on the job. Time is discrete. The model period is one month and is partial equilibrium. Workers are risk neutral and heterogeneous in terms of: (a) age, $t \in \{1, ..., T\}$, and (b) human capital, $x \in \{1, ..., X\}$. Workers transit between employment (E) and unemployment (U). While being employed (E), workers may switch from one job to another. Transition probabilities are defined as follows:

- Workers in unemployment find jobs with probability f_t
- Jobs are destroyed with probability s_t
- Employed individuals can find jobs with probability f_t^E

The above probabilities are exogenous and age-dependent. When unemployed, workers receive unemployment benefits (outside option) b_t. While working, workers receive wages $w_i(x, \epsilon_i) = y(x)\exp\{\epsilon_{i,t}\}$, $\epsilon_{i,t} \sim N(0, \sigma^2_{\epsilon,t})$. $y(x)$ is a monotonic function and ϵ is a match quality shock (fixed throughout the duration of a match).

While employed, human capital may appreciate by one unit each period with probability $\rho_{x,t}$. Human capital in our model may also depreciate (also by one unit) in two circumstances:

- When unemployed, with probability $\delta_{x,t}$
- When changing jobs, with probability $\kappa_{x,t}$

Workers seek to maximize the present value of earnings over their working life. The value function of a worker in unemployment is given by:

$$U(t,x) = b_t + \beta\,(1 - f_t)\,\mathbb{E}_{x'}U(t+1,x') + \beta f_t\,\mathbb{E}_{x',\epsilon}\max\{U(t+1,x'), W(t+1,x',\epsilon)\} \tag{1}$$

Equation 1 shows that workers form expectations about ϵ. Agents discount the future at a rate β. While unemployed, human capital x can only decrease so $x' \in \{x, \max\{x-1, 1\}\}$. The value function of a worker in employment is given by:

$$
\begin{aligned}
W(t,x,\epsilon) = y(x)\exp(\epsilon) & \\
+\beta\,(1-s_t) & \begin{bmatrix} (1-f_t^E)\,\mathbb{E}_{x'}W(t+1,x',\epsilon) \\ \\ \quad + f_t^E\,\mathbb{E}_{x',\eta}\max\{W(t+1,x',\eta),W(t+1,x',\epsilon)\} \end{bmatrix} \\
+\beta\,s_t & \begin{bmatrix} f_t\,\mathbb{E}_{x',\eta}\max\{U(t+1,x'),W(t+1,x',\eta)\} \\ \\ +(1-f_t)\,\mathbb{E}_{x'}U(t+1,x') \end{bmatrix}
\end{aligned}
\tag{2}
$$

Equation 2 states that when a worker is employed, human capital can decrease if changing jobs so $x' \in \{x, \max\{x-1, X\}\}$.[16] If the job is destroyed, workers are allowed to search for a job in that period. In a new job, a new realization of the match quality is created $\eta \neq \epsilon$.

In order to maximize the present value of earnings over their working life, workers choose between remaining in unemployment, staying in their current job or jumping to a new job, provided they receive the corresponding exogenous transition shocks. Workers ponder the potential loss in human capital from changing jobs or remaining in unemployment and, importantly, its impact in earnings, when deciding about their employment state. Also, they have uncertainty about the worker-firm quality match, which has an effect on earnings and affects the worker transition decision.

In our model, employment is an opportunity to increase human capital and hence earnings. Unemployment represents both an opportunity cost of increasing human capital while working and the additional cost of depreciating one's human capital. Last, changing jobs represents a trade-off between potentially finding a better worker-firm quality match -and higher earnings- and potentially losing some of the gained human capital during the transition.

4 Calibration

We estimate the model using a combination of datasets from the Chilean economy, including a novel dataset on posted job ads. We use a combination of CASEN and the Encuesta Nacional de Empleo (ENE) to compute a number of moments for the Chilean economy. The moments targeted in the estimation are:

- Profile of lifecycle wages (CASEN)[17]; 32 year-observations
- Returns to experience (www.trabajando.com & CASEN)[18]; 32 year-observations

[16] This assumption creates job-to-job transitions that result in wage losses.
[17] We take the estimates directly from Lagakos et al. (2018)
[18] This is a "hybrid" moment: the first 8 years are from www.trabajando.com, while the rest of the years are

- lifecycle profiles for E→U, U→E and J→J transitions (ENE); 32 year-observations each
- Average wage loss (%) after an E→U→E episode and average wage gain (%) after an J→J transition (ENE); 1 cross-sectional observation each

The profile of lifecycle wages are the percentage increase of wages relative to the wage at the beginning of the lifecycle.[19] The returns to experience are the percentage increase of wages relative to a job with no required experience. Lifecycle profiles for E→U, U→E and J→J transitions are the average yearly hazard of these transitions. The average wage loss (%) after an E→U→E observation is the workers' average percentage difference in wages after observing an E→U→E transition within a year. Finally, the average wage gain (%) after an J→J observation is the workers' average percentage increase in wages after observing an J→J transition within a year. In addition to these moments, we also compute and compare two more moments not targeted at estimation. These are the share of employment and non-employment over the lifecycle (ENE).

We smooth data observations by using polynomials in age of order 5 for all our lifecycle data moments: the profile of lifecycle wages, returns to experience, and lifecycle profiles for E→U, U→E and J→J transitions. The monotonic component of wages, $y(x)$, is specified as a linear interpolation of the ads lifecycle profiles. For the average wage loss (%) after an E→U→E episode, we compare one cross-sectional observation across the entire lifecycle. Also, for the average wage gain (%) after an J→J episode, we compare one cross-sectional observation across the entire lifecycle. For the rest of the moments, we use year-observations.

All parameters in our model are allowed to vary with age. The components $\rho_x, \kappa_x, \delta_x, f, s, f^E, b$ are each specified as a polynomial of order 2 of the form $z_t = z_1 + z_2\, t + z_3\, t^2$. For example, the probability of job separation has the following form: $s_t = s_1 + s_2\, t + s_3\, t^2$ at any given t over the lifecycle. The volatility component of the match quality shock is specified as $\sigma_{\epsilon,t} = \sqrt{\exp\{\sigma_{\epsilon,1} + \sigma_{\epsilon,2}\, t + \sigma_{\epsilon,3}\, t^2\}}$. We estimate parameters to match Chilean data moments to simulated data moments (Simulated Method of Moments). A model period is one month, hence, the lifecycle of an agent in the model consists of 420 periods. We exogenously set $\beta = 0.99$.

In order to choose the parameters, we minimize the distance between the moments generated by the model and their counterpart in the data. In particular, the calibration algorithm aims to minimize the sum of squared distance between earnings and transition profiles and those produced by the model using the simulated method of moments. Because some moments have different scale, or different number of observations, we impute some weights to each component as in Guvenen et al. (2015). See section A.1 in the Appendix for further details. Lifecycle averages of estimated parameter values over the lifecycle are presented in Table 3, along with the model fit. The complete set of calibrated parameters is presented in Table A1 in the Appendix, and the parameters' lifecycle

extrapolated using the growth rates implied in CASEN. See the complete description in Section 2.

[19] As in Lagakos et al. (2018).

Table 3: Calibration

Moment	Data	Model		Parameter	Average
J→J Hazard	0.15	0.14		$\bar{\rho}_x$	0.0140
U→E Hazard	0.49	0.49		$\bar{\kappa}_x$	0.0000
E→U Hazard	0.03	0.08		$\bar{\delta}_x$	0.0081
Employment Share	0.86	0.81		$\bar{\sigma}_\epsilon$	0.0230
Non-Employment Share	0.13	0.18		$\bar{f}_t$	0.4917
Returns to Experience (%)	0.75	0.76		$\bar{s}_t$	0.0809
Lifecycle Wages (%)	0.36	0.34		$\bar{f}_t^E$	0.9999
E→U→E Loss (%)	-0.04	-0.04		$\bar{b}$	-0.5753
J→J Gain (%)	0.02	0.02			

f

Notes: The left side of the table displays targeted average model moments against the data. These moments are described in Section 4. The right side of the table displays average parameter estimates of the model presented in Section 3. Table A1 in the Appendix displays the full set of parameter estimates. We use the SMM estimation method. Section A.1 in the Appendix describes further details about the estimation procedure.

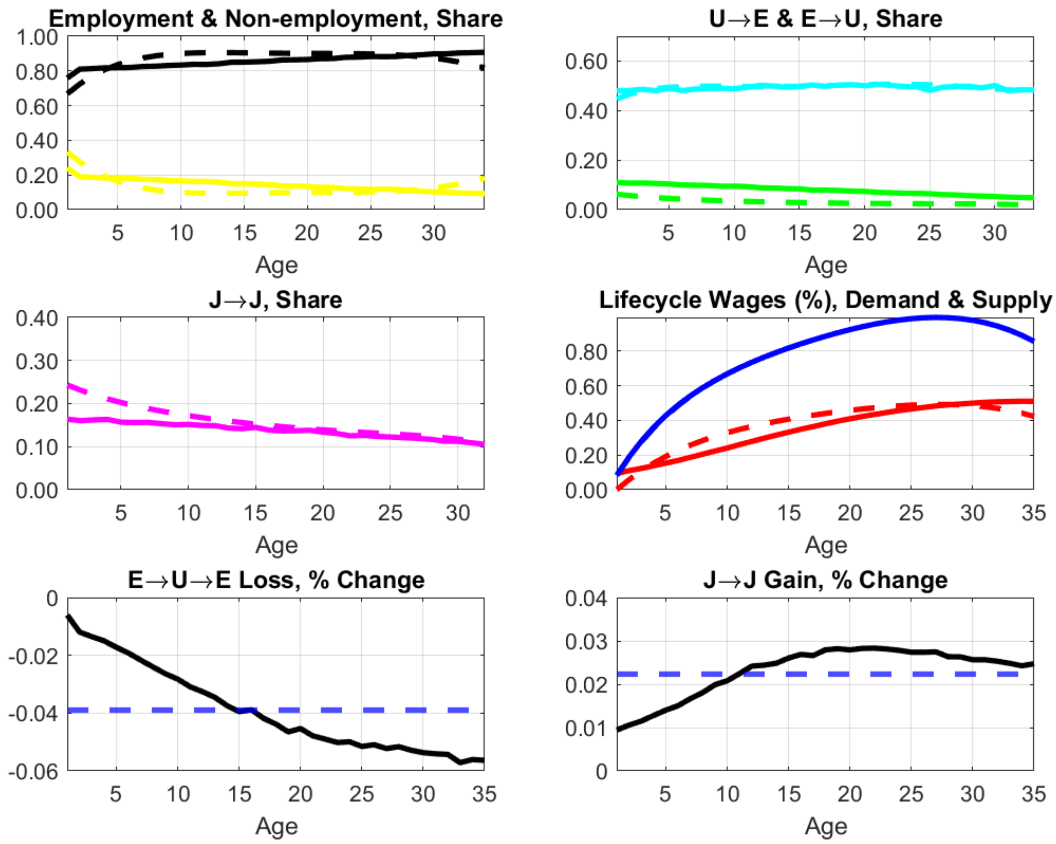
behaviour is displayed in Figure A2 in the Appendix.

4.1 Results

The average parameter of the probability of finding a job from unemployment $\bar{f}_t$, is estimated at 0.4917 and generates a model U→E transition hazard of 49% over the lifecycle. The probability to lose a job, s_t, is estimated to be substantially smaller; the parameters generate an average probability of separation of 0.0809 over the lifecycle, and it is declining in age. The average probability to upgrade one's human capital over the lifecycle is small, $\bar{\rho}_x = 0.0140$, and has an inverted U-shape. It grows until age 20 in the lifecycle and starts declining thereafter. It never exceeds a 2% monthly probability. By contrast, the probability to lose one unit of human capital from being in unemployment ($\bar{\delta}_x = 0.0081$) is small early in life and increasing throughout the lifecycle, reaching a maximum of around 0.0374 at the end of the working life.

The estimated parameters yield, noticeably, a 100% probability to find a job while being employed (f_t^E). In addition, there is an average probability to lose one unit of human capital while experiencing a job-to-job transition of $\bar{\kappa}_x = 0.00004$, which is increasing over age.[20] Finally, the outside option, b_t, is estimated to be decreasing over age.

[20]The average fraction of job movers that gain wages when experiencing a J→J transition is 98%. This is in part because in our model there is a small average probability of $\bar{\kappa}_x = 0.00004$ to suffer a loss of human capital when switching jobs.



Notes: The figure displays model moments fit against the data. The top left panel displays employment and non-employment shares over the lifecycle. The top right panel displays U→E & E→U transition rates over the lifecycle. The bottom middle panel displays J→J transition rates over the lifecycle. The middle right panel displays percentage increase of wages over the lifecycle (supply), and percentage increase of returns to required experience (demand). The bottom left panel displays the model E→U→E wage loss in percentage over the lifecycle (solid line) against the data average (dashed line). The bottom right panel displays the model J→J wage gain in percentage over the lifecycle (solid line) against the data average (dashed line).

Figure 2: Model Fit

4.2 Model Fit

The model fit can be observed in Table 3 and Figure 2. The model probabilities, f_t and s_t, generate the E→U and U→E transitions, which are very close to the data.[21] These moments are targeted at estimation. The model also generates the employment and non-employment shares over the lifecycle, close to the data, despite not being a target in the estimation.

Lifecycle earnings profiles, both from the worker side and the ads side, are well matched with our

[21] E→U transitions in Chile are similar to European countries, around 3 percent, and slightly above the US, which is around 1.4 percent. U→E transitions are a bit above the US and European averages (26 and 29 percent, respectively), but close to countries like Denmark and Sweden (42 and 43 percent, respectively). For more details, see Ward-Warmedinger and Macchiarelli (2013) and Molloy et al. (2016).

model. The increasing concave profile in these moments is partly obtained by an increasing concave accumulation of human capital (Figure A4 in the Appendix) that is generated both exogenously and endogenously in our model.[22] The bottom left panel of Figure 2 shows that we obtain an E→U→E wage loss (%) close to the data on average (around a 4% loss), but our moment is decreasing in age. This is because early in life workers have accumulated little human capital, hence a period of unemployment will not diminish significant human capital from the worker. Late in life it is when workers face the largest risk of losing earnings, as it is the case where they can lose their accumulated human capital.

A moment that we also target at estimation is the job-to-job wage gain (%), which in the data is slightly above 2%. Our model is close to the data, particularly late in life. In our model, job-to-job wage gains are only generated from the misallocation between the firm-worker match. Workers endogenously choose to remain in a firm if their earnings, which are affected by the firm-worker match quality shock, are larger than the average draw. Alternatively, they leave a firm if they expect to draw a larger firm-worker match in a new job.

Finally, the model also matches the declining pattern of job-to-job transitions. The middle left panel in Figure 2 shows that J→J transitions in the data decline over the lifecycle from 24% at the beginning to 10% at the end.[23] In our model, we generate a somewhat flatter profile from 17% at the beginning to 10% at the end of the lifecycle. Our model generates an average 14% J→J hazard, which is close to the data (13%), despite estimating a high probability to find a job while being employed, $\bar{f}_t^E = 0.9999$. This is because a significant fraction of workers in our model endogenously choose to remain at their current jobs.

5 Counterfactual Analysis

Given that the model performs a reasonable fit across employment transitions and wage growth, in the following we use counterfactual experiments to gain a deeper understanding of the contribution of different factors to the mismatch in the worker vs. ads wage growth. More specifically, we perform simulation exercises using our baseline estimated model in order to disentangle the contribution to the workers vs. job ads growth gap that is due to frictions in the "learning" process or standard labour market frictions.

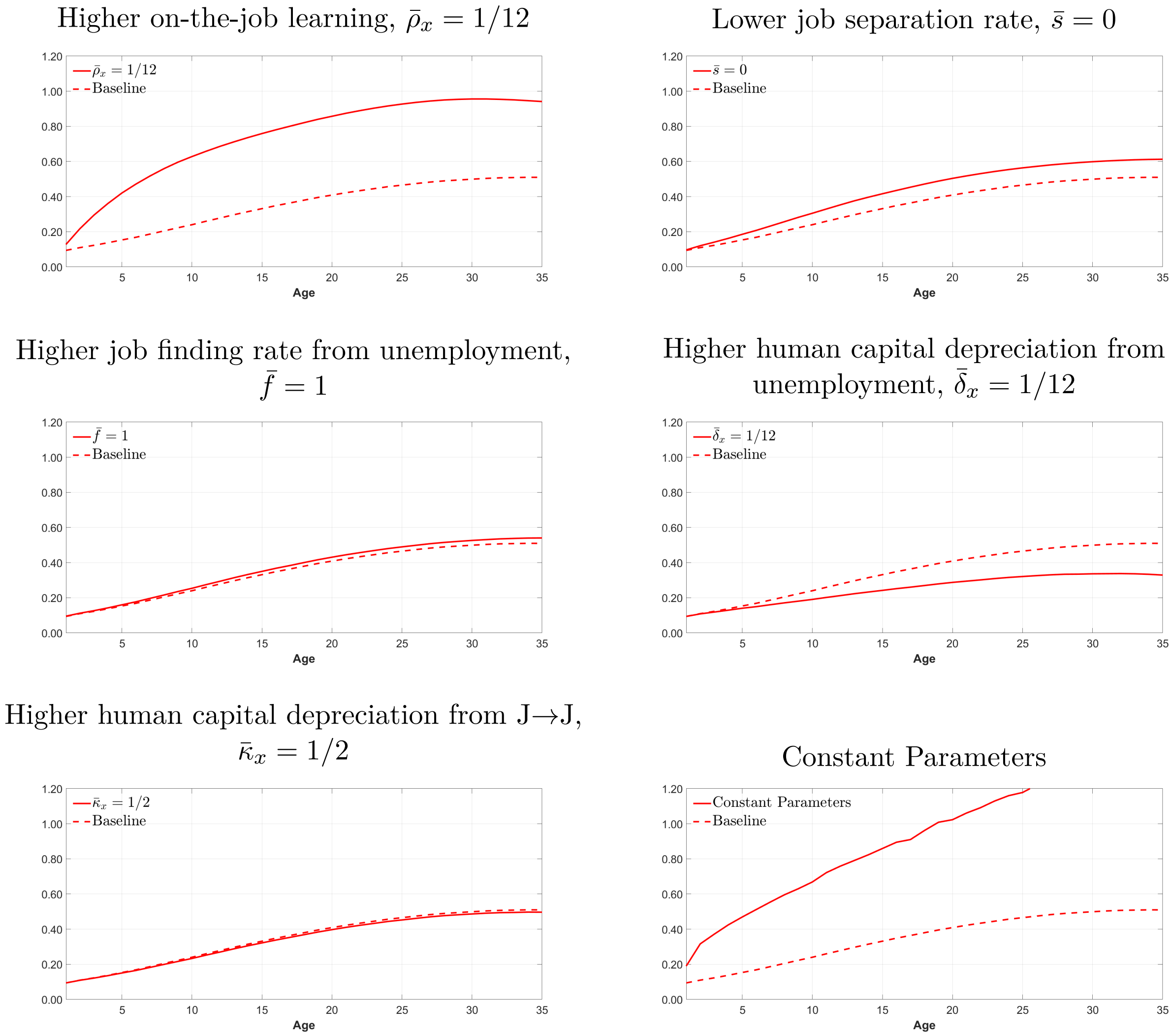
5.1 Simulations

We take our calibrated model and input different parameters (one at a time) to the different components of our model in order to see how lifecycle wages respond. We perform a total of six simulation exercises.

First, we increase the average probability of increasing one unit of human capital, ρ_x, to see

[22]Exogenously as in estimating a concave profile in ρ_x, and endogenously as the worker will choose to avoid unemployment and job-to-job transitions so that human capital does not depreciate.

[23]Chilean J→J transitions are similar to the US, with a 1975-2014 yearly average of 14 percent. For more details, see Molloy et al. (2016).



Notes: The figure displays lifecycle wages for different counterfactuals, compared to our baseline estimation. The top left panel displays lifecycle wages for a model with $\bar{\rho}_x = 0.1$ over the lifecycle. The top right panel displays lifecycle wages for a model with $\bar{\delta}_x = 0.1$ over the lifecycle. The middle left panel displays lifecycle wages for a model with $\bar{\kappa}_x = 0.5$ over the lifecycle. The middle right panel displays lifecycle wages for a model with all parameters constant (at their lifecycle average value) over the lifecycle. The bottom left panel displays lifecycle wages for a model with $\bar{s} = 0$ over the lifecycle. The bottom right panel displays lifecycle wages for a model with $\bar{f} = 1$ over the lifecycle.

Figure 3: Simulations, Lifecycle Wages (%), Supply

how higher accumulation of human capital affects wages. In our estimation, ρ_x was estimated at a lifecycle average monthly probability of 0.0140. In annual terms, this would be a probability of 0.17 on average to increase human capital in any given year. In this simulation exercise we increase this probability from 0.0126 to 1/12 so that the annual probability to increase one's human capital is equal to 1. As Figure 3 shows, lifecycle wages jump upwards, reaching around twice the wage growth at the end of the lifecycle relative to our estimated model (and the data), specifically around 90 percent. Interestingly, the resulting lifecycle profile is similar to the profiles documented for the

US and UK in Lagakos et al. (2018).[24] Figure A5 in the Appendix shows that this increase in wages comes through higher human capital accumulation. In our model, wages are directly affected by a monotonic function on human capital, $y(x)$. Hence, the higher the probability to accumulate and increase human capital, the higher lifecycle wage growth.

Second, we decrease the average probability of job separation, s_t, to an extreme to see how labor market frictions affect wages. In our estimation, s_t was estimated at a lifecycle average monthly probability of 0.0809. This is a high separation rate. It implies that jobs are destroyed approximately every 11 months on average. In this simulation exercise we decrease this probability from 0.0809 to 0, so that there is no job destruction whatsoever. As Figure 3 shows, lifecycle wages jump upwards, but only from 0.50 in our model to 0.61 at the end of the lifecycle. In this simulation, workers remain at work and at most switch from job-to-job, but never experience unemployment (see Figure A6 in the Appendix). Therefore, there is no depreciation in human capital from unemployment and, as workers remain permanently employed, an ongoing probability to increase human capital on the job produces this result. Noticeably, the complete elimination of this type of labour market friction produces a relatively lower effect on wages than the simulation with $\bar{\rho}_x = 1/12$.

Our third simulation also eliminates labour market frictions through the job finding rate from unemployment, f_t. In our estimation, f_t was estimated at a lifecycle average monthly probability of 0.4917. Again, this is a high finding rate. It implies that an unemployed worker finds a job approximately once every two periods in unemployment, on average. In this simulation exercise we increase this probability to 1, so that workers do not remain in unemployment beyond 1 period. Figure 3 shows a small lifecycle wage jump upwards. Given that the finding rate was already high at the estimation, the small effect of the simulation is not surprising. Most moments of our model barely change (see Figure A7 in the Appendix). As a consequence, eliminating frictions from job separation, and not job finding, is more important for lifecycle wages in Chile.

Fourth, we increase the average probability of losing one unit of human capital when workers are unemployed, $\delta_{x,t}$, to see how the loss of human capital through unemployment affects wages over the lifecycle. In our estimation, $\delta_{x,t}$ was estimated at a lifecycle average monthly probability of 0.0081. In this counterfactual exercise we increase this probability to 1/12 so that the annual average probability to decrease one's human capital is equal to 1 if the worker remains the whole year in unemployment. As Figure 3 shows, lifecycle wages shift downwards, almost half the wage growth at the end of the lifecycle relative to our estimated model (and the data). Figure A8 in the Appendix shows that this decrease in wages comes through lower accumulation of human capital over the lifecycle, since the hazard of unemployment can destroy part of the accumulated human

[24] Their panel A of Table 2 reports summary statistics for developed countries. Germany's profile is the steepest, reaching 105 percent by 20-24 years of experience. This is followed by the United States (90 percent), the United Kingdom (85 percent), and Canada (80 percent).

capital. Hence, the higher the chance to lose human capital when unemployed, the lower lifecycle wage growth.

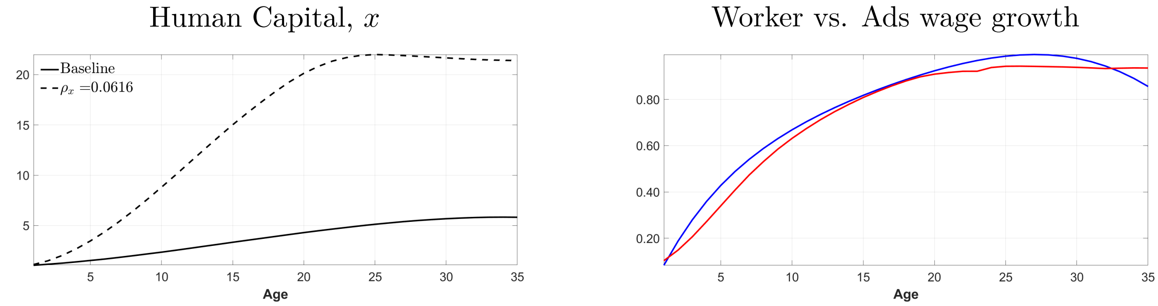
Fifth, we increase the lifecycle average monthly probability of losing one unit of human capital when workers transit from job-to-job, $\kappa_{x,t}$, to see how the loss of human capital through job-to-job affects wages over the lifecycle. In our estimation, $\kappa_{x,t}$ was estimated at a lifecycle average of 0.00004. In this simulation exercise we increase this probability to 1/2 so that one in two J→J transitions decrease a unit of human capital. As Figure 3 shows, lifecycle wages shift downwards, above half the wage growth at the end of the lifecycle relative to our estimated model (and the data). Figure A9 in the Appendix shows that this decrease in wages comes from lower human capital accumulation over the lifecycle, but also generates lower Employment shares and J→J transitions early in the lifecycle. Hence, the higher the chance to lose human capital when switching jobs, the lower the lifecycle wage growth. The loss in wage growth from a higher probability to lose human capital through a job-to-job transition, $\kappa_{x,t}$, appears to be substantially lower than the wage loss from a higher probability to lose human capital at the incidence of unemployment, $\delta_{x,t}$. This is because job-to-job transitions are rare, while unemployment is more likely and can persist for a few months.

Finally, in our sixth simulation we use constant, age-unvarying parameters for all the components of our model, to see how the model wages would respond over the lifecycle. In this counterfactual exercise we use constant parameters at their lifecycle average values. As Figure 3 shows, lifecycle wages grow linearly, without a concave shape over the lifecycle. Figure A10 in the Appendix shows that this linear behavior is the case for most moments of the model over the lifecycle. Thus, without age varing parameters the model is unable to capture well the nonlinear patterns in the data. We interpret this simulation as an indication that there are lifecycle effects in the accumulation of human capital. In particular, lifecycle effects are important for the shape of wages in the latter parts of the lifecycle.

5.2 Counterfactual: closing the worker vs. ads wage growth mismatch

We also want to look at how much of the worker vs. ads wage growth mismatch can be attributed to failure-to-learn. In the data, job ads wage growth is two times the worker wage growth at the end of the lifecycle. We pose the following question: how much can failure-to-learn explain this fact? We address this question by closing the gap between worker vs. ads wage growth over the lifecycle. Failure-to-learn in our model corresponds to the probability to increase human capital, $\rho_{x,t}$. The estimation of our model yielded an average 0.0140 monthly probability to increase human capital over the lifecycle in our model. Thus, we keep all parameters from the baseline estimation fixed and change the parameters pertaining to the accumulation of human capital, $\rho_{x,t}$, such that lifecycle wages from the worker side match the increase of wages from the demand side (job ads).

This exercise yields a lifecycle average monthly probability of $\bar{\rho}_x = 0.0616$, around four times



Notes: The left panel displays human capital accumulation, x, over the lifecycle for our baseline model (solid line) and the counterfactual exercise ($\rho_x = 0.0544$) where worker and ads wage growth are equal (dashed line). The right panel displays worker (red) vs. ads (blue) wage growth for this counterfactual exercise ($\rho_x = 0.0544$).

Figure 4: Counterfactual: closing the worker vs. ads wage growth mismatch

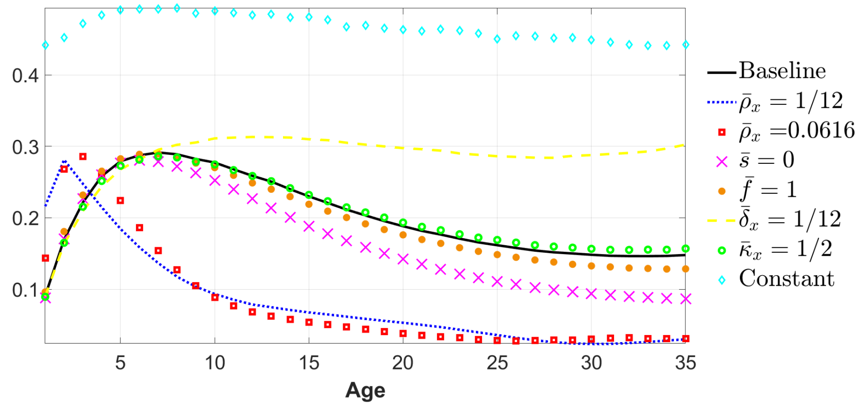
the probability to increase one's human capital in our baseline estimation, but slightly below 1/12. The counterfactual exercise matches supply (workers) and demand (firms) wage growth over the lifecycle as can be seen on the right panel of Figure 4. Strikingly, human capital accumulation grows much more faster in this model relative to our baseline. The left panel of Figure 4 shows that human capital accumulation in this model reaches a value of slightly above 20 at the end of the lifecycle. Again, four times higher relative to our baseline estimation. The rest of the moments of this counterfactual model remain barely unchanged (see figure A11 in the Appendix). Hence, failure-to-learn, 4 times below the level where worker vs. ads wage growth matches can explain this gap.

Both the simulation (in the previous subsection) and the counterfactual exercises show that on-the-job learning, human capital depreciation and labour market frictions affect wages. What is less known is how inequality of earnings is affected by the process of accumulation of human capital. The amount of inequality of lifetime earnings is important as it has implications for welfare.[25] Our model allows us to observe the distribution of workers' earnings throughout the lifecycle. We are now interested in looking at the Gini coefficients of each simulated (and counterfactual) economy.

Figure 5 displays such coefficients. Our baseline estimation (black solid line) generates an increase of inequality during the first 5-7 years starting from a coefficient of 0.09 to a coefficient of 0.30. After the first 5-7 years, inequality starts declining throughout the lifecycle, reaching a final value above 0.15. In our model, inequality increases during the first years since all workers start with the same level of human capital, and their only heterogeneity comes from the firm-match idiosyncratic component, ϵ_i. There are no other sources of observed or unobserved heterogeneity.[26] Early in life, the probability to increase human capital is low, so a few lucky workers increase their human capital and hence increase their earnings, while most workers remain with the initial human

[25]The question of welfare costs was first addressed by Attanasio and Davis (1996).

[26]See Huggett et al. (2011) for the importance of preexisting initial conditions for earnings and consumption heterogeneity over the lifecycle. Also, Blundell et al. (2015) show the importance of accounting for unobserved heterogeneity by education over the lifecycle.



Notes: The figure displays gini coefficients for workers' wages over the lifecycle for each simulated (counterfactual) economy. The black solid line (—) displays the gini coefficients for our baseline estimation. The blue dotted line (····) displays the gini coefficients for the economy where $\rho_x = 1/12$. The yellow dashed line (- - -) displays the gini coefficients for the economy where $\bar{\delta}_x = 1/12$. The green circles (○) display the gini coefficients for the economy where $\bar{\kappa}_x = 1/2$. The cyan diamonds (◇) display the gini coefficients for the economy where parameters are constant (equal to their lifecycle average). The magenta crosses (×) display the gini coefficients for the economy where $\bar{s} = 0$. The orange circles (●) display the gini coefficients for the economy where $\bar{f} = 1$. The red squares (□) display the gini coefficients for the economy where $\bar{\rho}_x = 0544$ (no gap between worker vs. ads wage growth).

Figure 5: Lifecycle Gini coefficients for each Economy

capital. After year 7, and when the probability to increase human capital becomes larger and larger, most workers start catching-up increasing their human capital, and hence inequality starts to decrease.

The simulated economy with $\bar{\rho}_x = 1/12$ (blue dotted line) has a larger probability to accumulate human capital. This generates larger accumulation of human capital and larger wage growth for workers over the lifecycle. As Figure 5 shows, after the initial increase in earnings inequality after 2 years, the gini coefficients start declining over the lifecycle. In this economy, human capital grows the fastest for all workers and, as a consequence, earnings inequality is the lowest at the end of the lifecycle. Also, the economy with the counterfactual exercise where the gap between workers and ads wage growth is closed, $\bar{\rho}_x = 0.0616$ (red squares), displays a similar pattern. This shows that the required level of human capital to meet demand would produce much lower labour earnings inequality throughout the lifecycle. The cross-sectional average of the gini coefficients in our baseline equals 0.22, while in the counterfactual this number is 0.0838, around 3 times lower.

We can also comment on the inequality generated by the economies without labour market frictions. We showed in Section 5.1 that the probability of finding a job from unemployment was high in the estimation of our model, hence eliminating this type of friction ($\bar{f} = 1$, ●) generates little changes. Figure 5 shows that there are little differences with respect to our baseline estimation. What is in stark contrast is the frictions generated by job separation. When we eliminate job separation ($\bar{s} = 0$, ×) inequality is reduced. In our model, there is depreciation of human capital when unemployed, besides the opportunity cost of not learning on the job. Still, when this friction is completely eliminated, the decrease of inequality is not as large as in the economy where the probability to augment human capital is slightly larger ($\bar{\rho}_x = 1/12$ or $\bar{\rho}_x = 0.0616$).

The simulated economies where we increase the probability to lose human capital through either unemployment or J→J ($\delta_x = 1/12$, (yellow dashed line), and $\kappa_x = 1/2$, (green circles), respectively) display higher earnings inequality throughout the lifecycle with respect to our baseline. This shows that the loss of human capital by any of these incidences creates higher earnings inequality.

The simulated economy that has parameters constant at their average lifecycle value (cyan diamonds) produces gini coefficients over the lifecycle that are somewhat constant. This simulated economy has the highest inequality of all the economies that we have displayed. The reason is that in our estimated baseline model the lifecycle effect of $\delta_{x,t}$ and $\kappa_{x,t}$ is present late in life and it is almost nonexistent early in the lifecycle. In this constant economy the parameter values are taken to their lifecycle average, meaning that human capital loss can occur equally at any point during the lifecycle. Hence, the constant pattern and the larger earnings inequality.

To sum up, we estimate human capital in our baseline Chilean economy to be 4 times below the level where supply meets demand, generating around 3 times higher labour earnings inequality. Whereas labour market frictions are not capable to close the wage vs. job ads growth gap alone, the on-the-job learning component is a much more important component.

6 Conclusion

In this paper, we use a novel dataset that allows us to estimate effective returns to experience. We observe that returns to experience is significantly larger than wage profiles for workers over the lifecycle. We propose a standard structural labour supply model to start thinking about what type of labour market frictions can explain the observed returns vs. wage profiles gap.

The estimation and the simulation exercises that we perform indicate that standard labour market frictions, such as the finding rate and the job separation rate, have limited capacity in explaining the difference between returns and wage profiles. In our model, it is the failure to upgrade one's human capital while remaining at work that has greater importance in explaining this gap. A counterfactual exercise shows that an improvement in the component of on-the-job learning would close this gap, not only increasing average wage profiles, but also decreasing labour market earnings inequality. Our results, namely that lifecycle wage heterogeneity is due mostly as a failure-to-learn, is related to Lagakos et al. (2018) and suggests that human capital accumulation stories are the ones to be looked at.

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Appendix

A.1 Estimation

We simulate lifecycle employment histories for 5,000 workers that enter the labour market and remain in the market for 35 years. The minimum distance estimator that we use is given by:

$$\hat{\theta} = \underset{\theta}{argmin} \boldsymbol{F}(\theta)' I \boldsymbol{F}(\theta) \tag{A.3}$$

$$F(\theta)_n = \frac{f_n(\theta) - m_n}{\omega_n}, \tag{A.4}$$

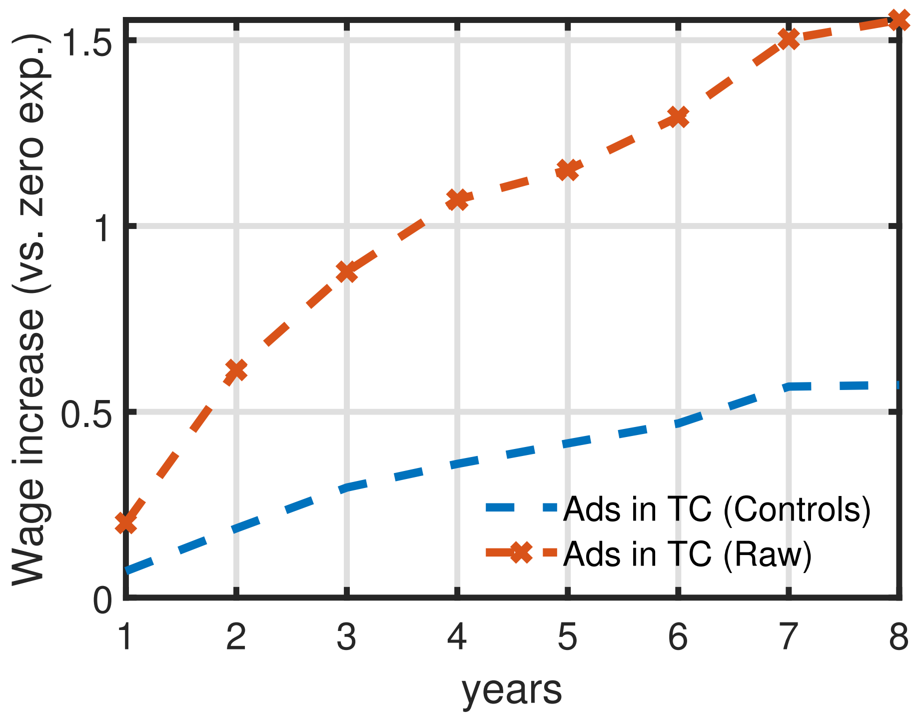
where $f_n(\theta)$ is the n^{th} model moment, and m_n is the corresponding n^{th} data moment. Similar to Sanchez and Wellschmied (2020) and Guvenen et al. (2015), we employ moment specific adjustment factors, ω_n. We use these adjustment factors to jointly deal with two issues presented by the data. First, the moments are measured on different scales. For example, employment share (%) is in absolute value about 30 times larger than the E→U hazard. If we had minimized the sum of absolute squared deviations ($\omega_n = 1$), the optimization would not have had put any emphasis on moments with low absolute sizes. At the same time, we have several moments which are close to zero, such as the E→U→E wage loss (%) or the J→J wage gain (%), but fluctuate substantially in relative terms from one age to the next. Hence, if we had minimized the sum of relative squared deviations ($\omega_n = abs(m_n)$), the optimization would have concentrated almost exclusively on these large relative deviations close to zero.

Using moment specific adjustment factors allows us to use absolute deviations but reduce the emphasis on moments with large absolute numbers. Unfortunately, it gives us a degree of discretion. We choose the adjustment factors in an iterative fashion such that the implied loss function is consistent with the model fit we observe in Figures 2 and A4.

At the estimation, we first obtain reasonable starting values by experimenting with different combinations of parameters. We tested different global minimum algorithms and a pattern search algorithm performed best in finding a minimum. Provided the optimal parameters, we compare the minimum to (possibly) other minima where we start the algorithm from different starting points.

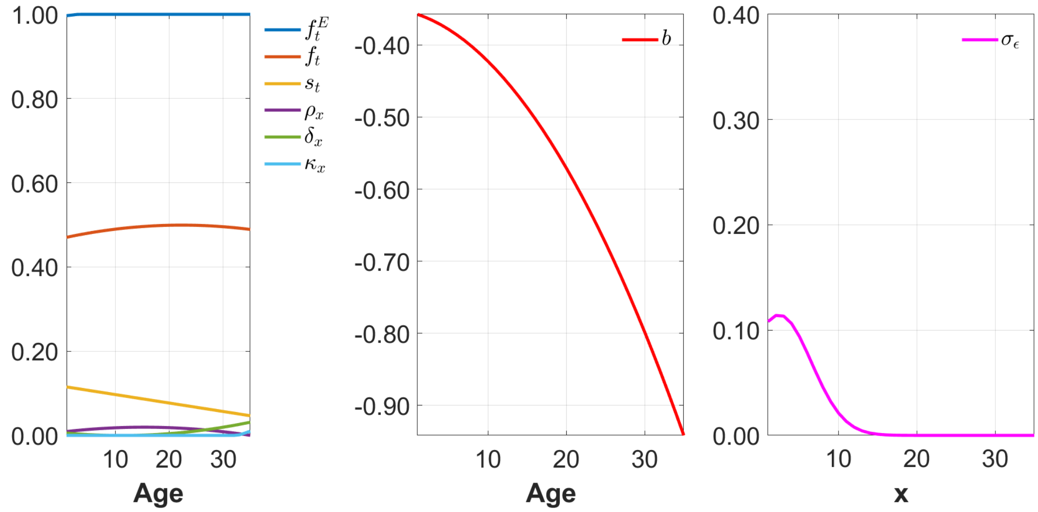
We find that the pattern search algorithm, in general, is able to converge to the same minimum from different starting points.

A.2 Additional Figures



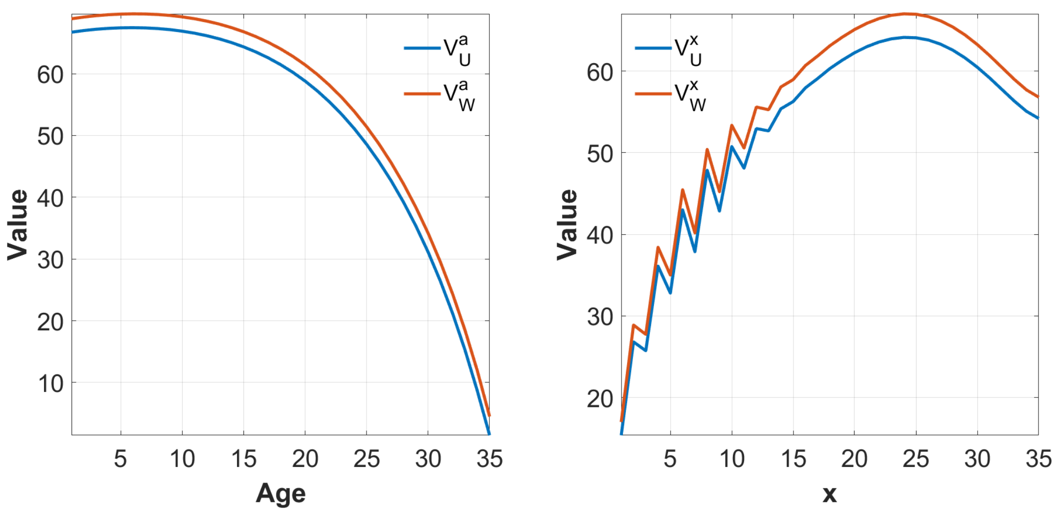
Notes: The red dashed line displays the ads' average posted wages increase (%) for the first 8 years of required experience from the raw TC data. The blue dash line displays the ads' residual average posted wages increase (%) after controlling by firms and job title fixed effects.

Figure A1: Wage Controls



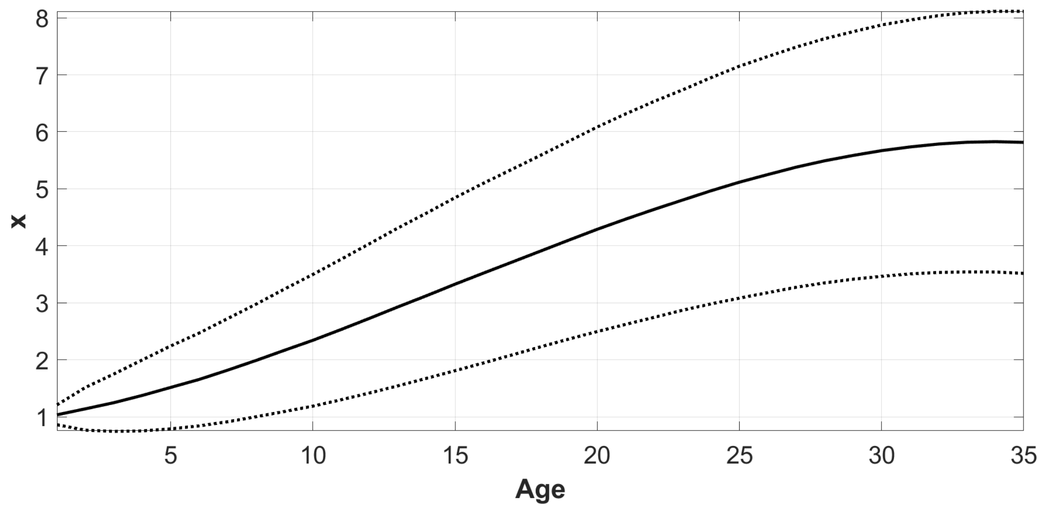
Notes: The figure displays model features from our baseline estimation.

Figure A2: Model Features



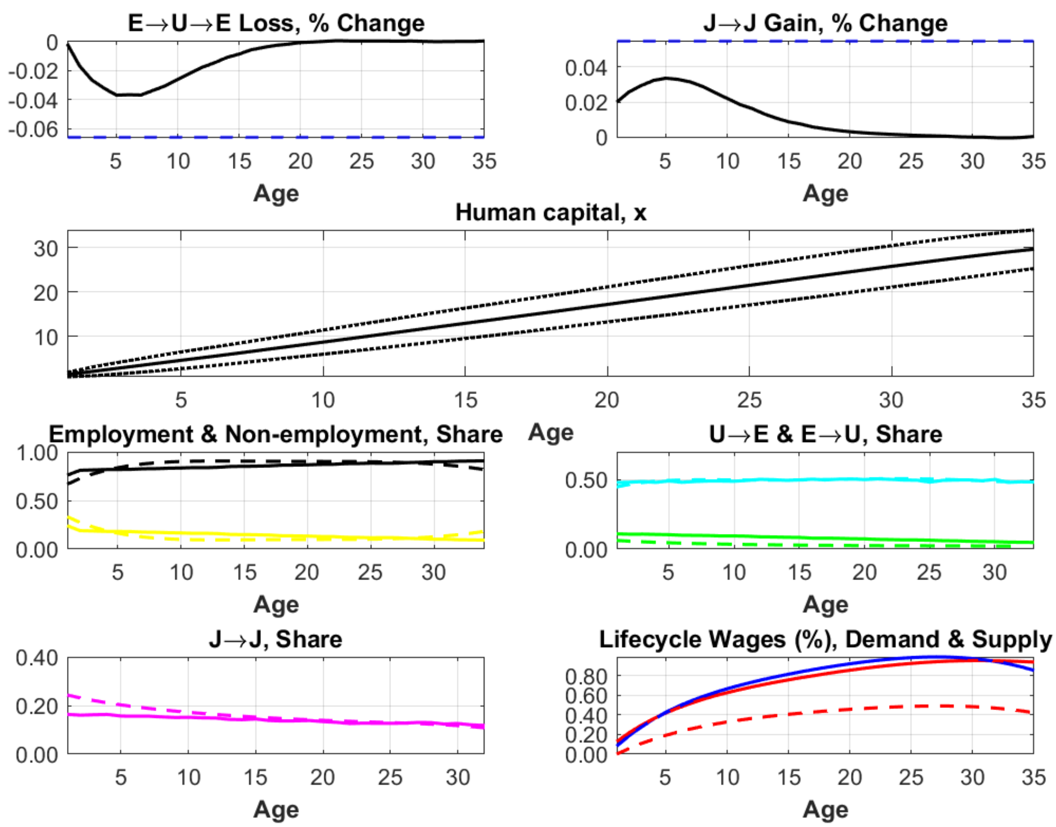
Notes: The figure displays the model's value functions for unemployment and employment over age (left panel) and human capital (right panel) for our baseline estimation.

Figure A3: Value Functions



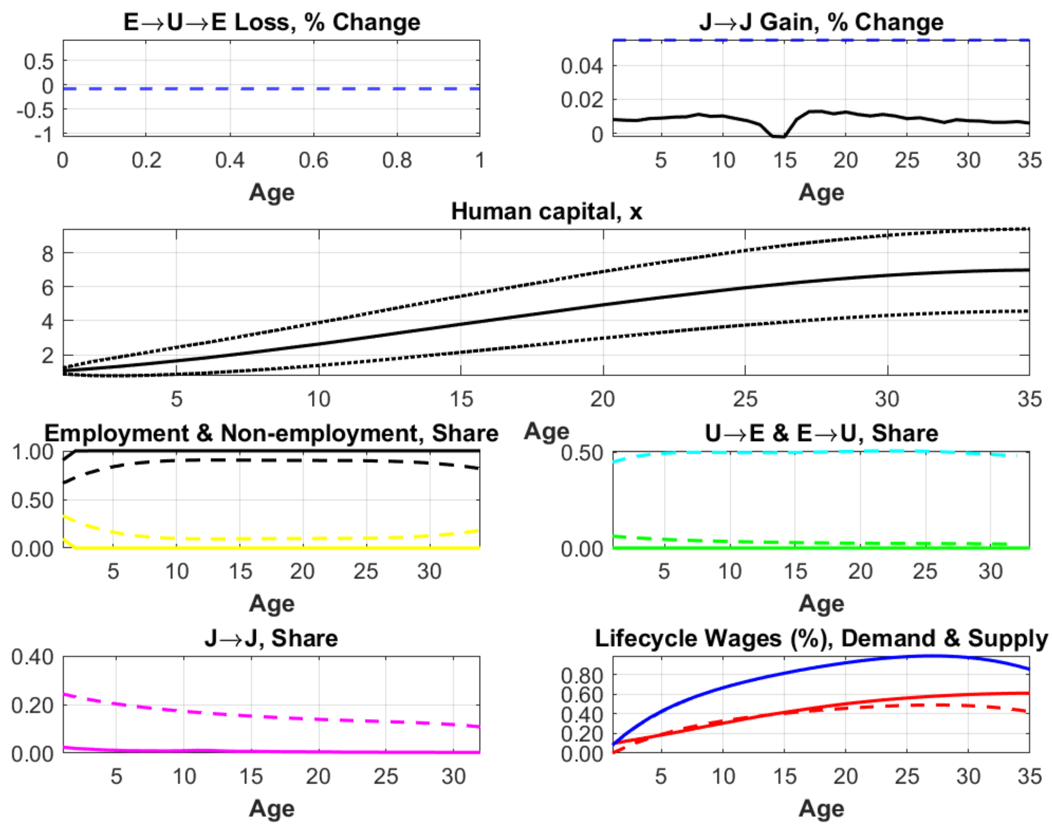
Notes: The bottom panel displays the average human capital (x) over the lifecycle (solid line) and 2 std. deviations (dashed lines).

Figure A4: Human capital over the lifecycle



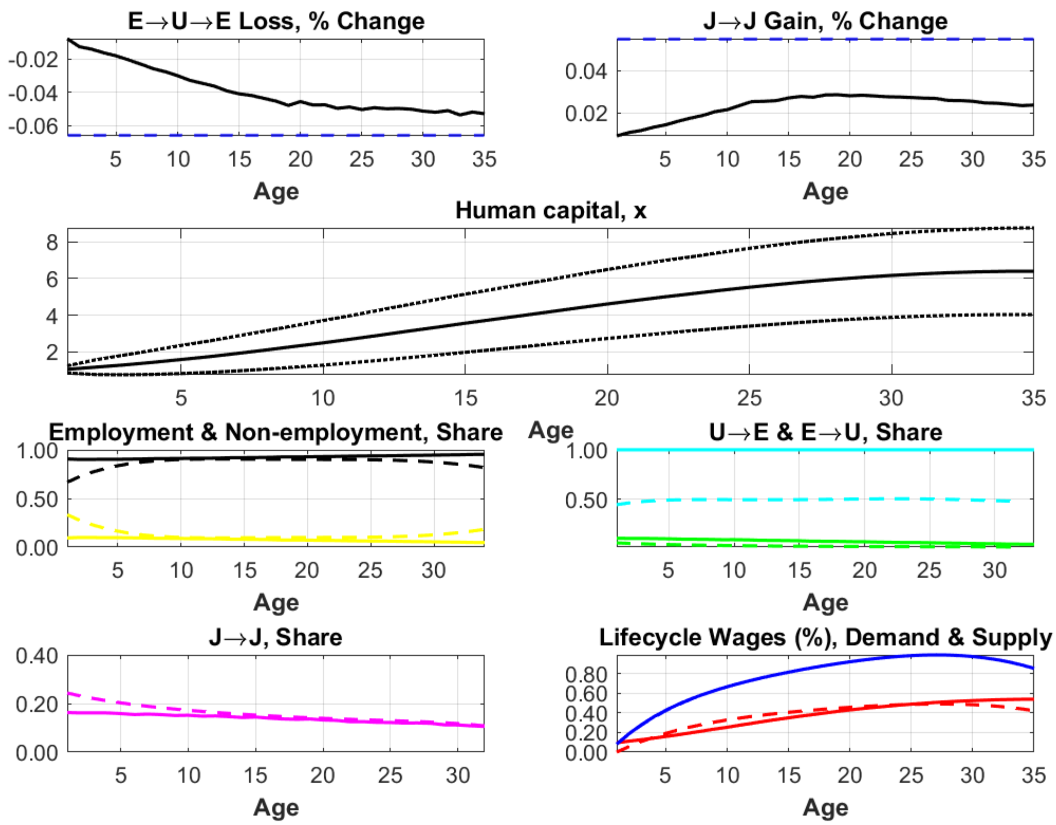
Notes: The figure displays the simulation ($\bar{\rho}_x = 0.10$) model response against the data.

Figure A5: Higher on-the-job learning, $\bar{\rho}_x = 1/12$



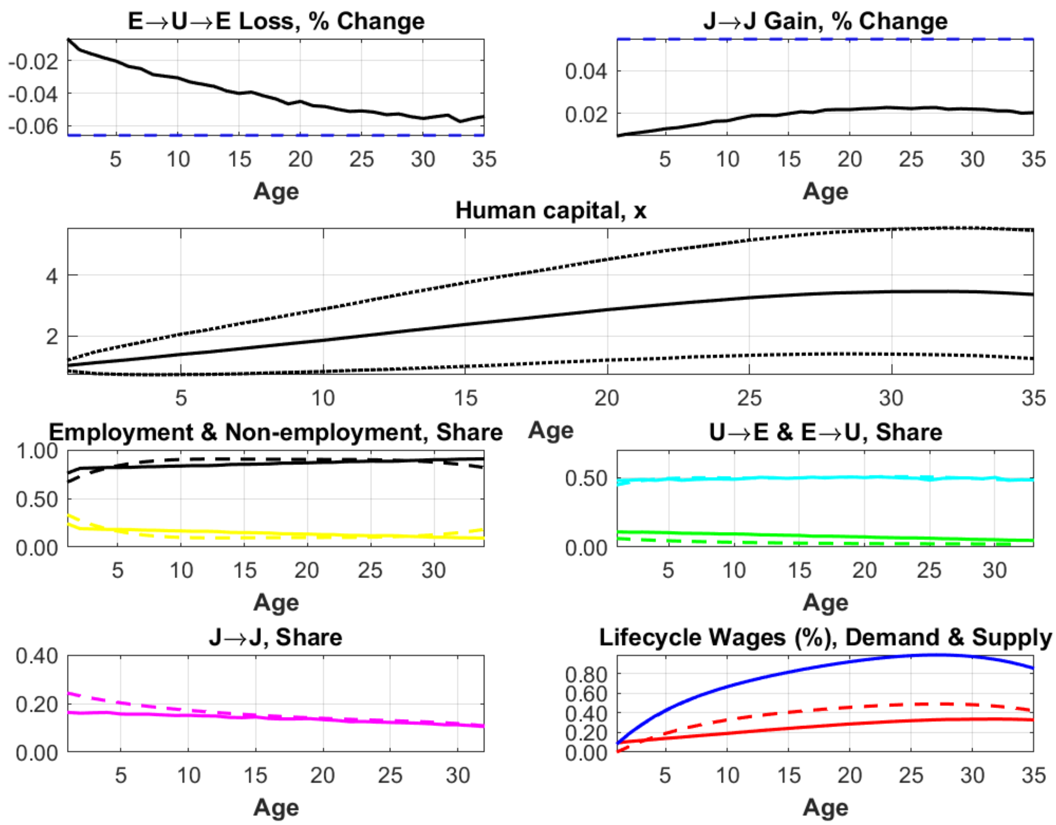
Notes: The figure displays the simulation ($\bar{s} = 0.00$) model response against the data.

Figure A6: Lower job separation rate, $\bar{s} = 0.00$



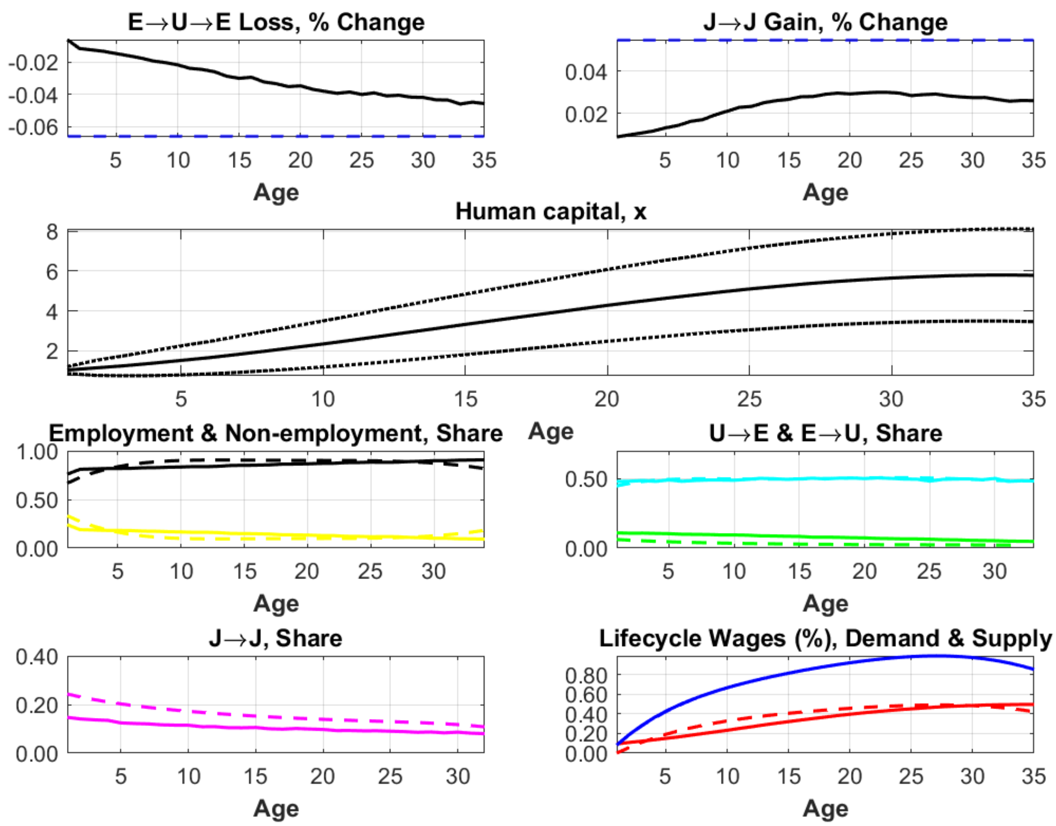
Notes: The figure displays the simulation ($\bar{f} = 1.00$) model response against the data.

Figure A7: Higher job finding rate from unemployment, $\bar{f} = 1.00$



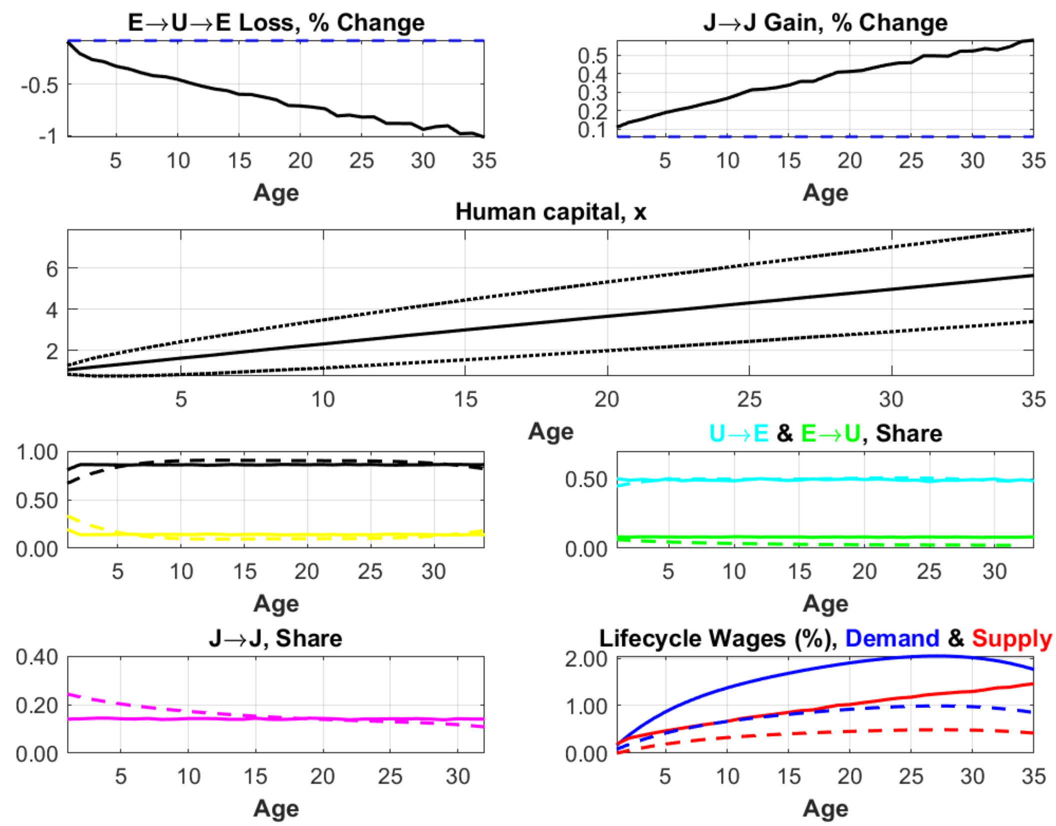
Notes: The figure displays the simulation ($\bar{\delta}_x = 0.10$) model response against the data.

Figure A8: Higher human capital depreciation from unemployment, $\bar{\delta}_x = 1/12$



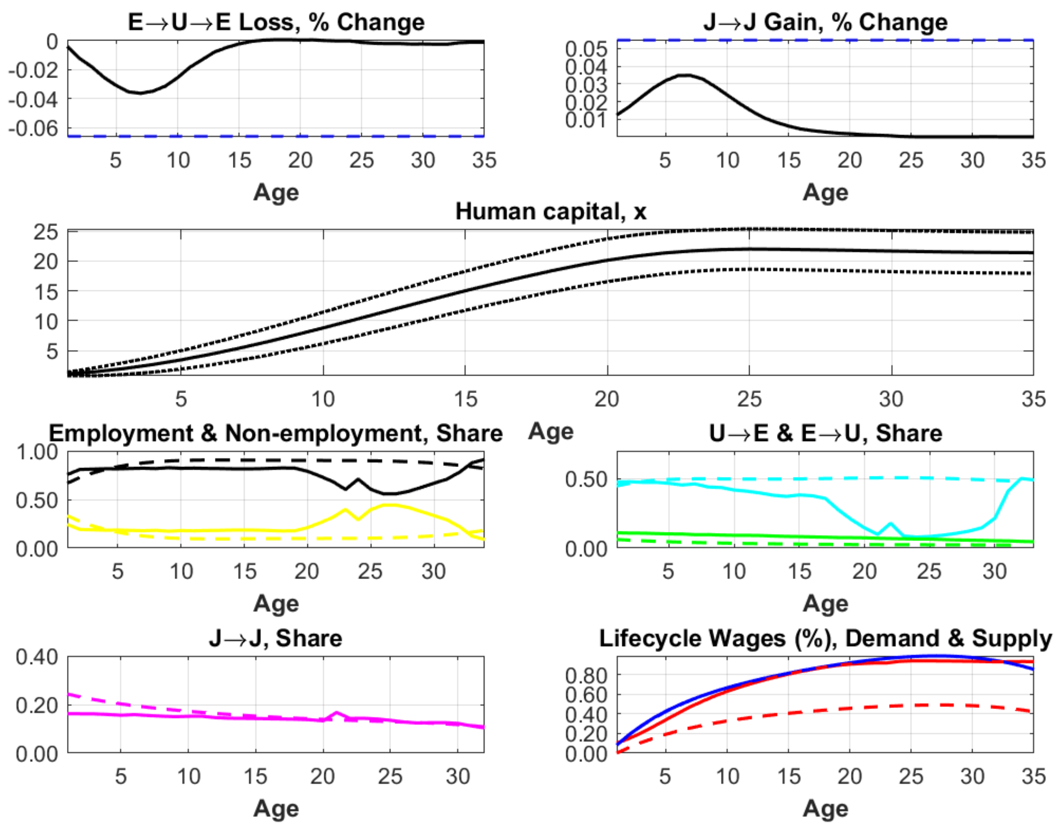
Notes: The figure displays the simulation ($\bar{\kappa}_x = 0.50$) model response against the data.

Figure A9: Higher human capital depreciation from J→J, $\bar{\kappa}_x = 0.50$



Notes: The figure displays the simulation (constant parameters at their lifecycle average values) model response against the data.

Figure A10: Age-unvarying Parameters



Notes: The figure displays the counterfactual ($\rho_x = 0.0544$) of closing the worker vs. ads wage growth gap.

Figure A11: Counterfactual: closing the worker vs. ads wage growth gap

A.3 Additional Tables

Table A1: Parameter Estimates

$\rho_{x,1}$	0.0077	f_1	0.4676
$\rho_{x,2}$	0.0015	f_2	0.0028
$\rho_{x,3}$	-0.0001	f_3	-0.0001
$\kappa_{x,1}$	0.0001	s_1	0.1171
$\kappa_{x,2}$	-0.0040	s_2	-0.0020
$\kappa_{x,3}$	0.0001	s_3	0
$\delta_{x,1}$	0.0067	f_1^E	0.9957
$\delta_{x,2}$	-0.0012	f_2^E	0.0010
$\delta_{x,3}$	0.0001	f_3^E	0.0001
$\sigma_{\epsilon,1}$	-4.6717	b_1	0.1487
$\sigma_{\epsilon,2}$	0.2808	b_2	-0.0031
$\sigma_{\epsilon,3}$	-0.0584	b_3	-0.0003

Notes: The table displays parameter estimates of the model presented in Section 3. We use the SMM estimation method.