Lifetime inequality measures for an emerging economy: The case of Chile ☆

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HIGHLIGHTS

- In the Chilean economy, lifetime inequality is as high as cross-section inequality.
- High lifetime inequality is due to lack of mobility in skilled and unskilled workers.
- Lifetime welfare is higher for skilled workers compared with unskilled workers.

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ABSTRACT

Even though the Chilean economy has experienced a sustained economic growth and made enormous progress in reducing poverty in the last 25 years, its income inequality continues to be among the highest in the world. Given its importance, the literature has paid considerable attention to income inequality in Chile. Nevertheless, all of the existing studies use a cross-section distribution of earnings when analyzing inequality. Cross-section and lifetime measures of inequality are different. While the latter reflects long run resources available to individuals, the former does not. This emphasizes the dynamic dimension of inequality. This paper focuses on the analysis of income inequality from a lifetime perspective for the Chilean economy using a search-theoretic framework. The model, which is structurally estimated with Chilean data, captures the dynamic of the labor market of male workers actively participating in the market and is used to simulate careers to construct lifetime measures of inequality. The results indicate that inequality is not only high in a cross-section perspective, but also in a lifetime perspective; and that low mobility is the main source of lifetime inequality in the Chilean labor market. Hence, regulation of the labor market matters because it affects the degree of mobility in the market.

1. Introduction

Since its return to democracy in 1990, the Chilean economy has experienced a significant and sustained economic growth, which has resulted in an average per capita GDP growth rate of 4.1% during the 1991–2011 period. This high economic growth experienced during these 20 years far exceeded the world's average per capita growth (1.4%) and the OECD's average per capita growth (1.6%). This important economic progress, combined with an increased social expenditure particularly targeting lower income households, has helped to reduce the absolute poverty from 38.6% in 1990 to 14.4% in 2011 (Gammage et al., 2014). Despite these important advances, the income distribution in Chile has not improved and it continues to be among the most unequal in Latin America, a region with the highest level of inequality in the world. Furthermore, in the late 2000s, Chile's Gini coefficient exceeded the average Gini coefficient for OECD countries (excluding Chile) by 14 points.[1]

In the last decade, there has been an ongoing discussion on the decreasing trend of income inequality in Chile, but any consensus on this issue is far from being achieved. When the Gini coefficient

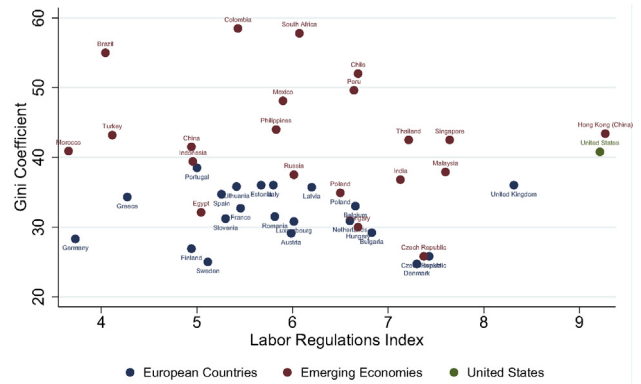[1] Chile became an OECD member on May 7th, 2010.

is used, inequality decreased from 57.2 observed in 1990 to 55.2 in 2000 and even further to 50.8 in 2011. Despite the improvement, the level of this indicator is still high. When an alternative indicator of inequality is used, the level of inequality shows an increase in the last 20 years. In effect, in 1990 the income of the wealthiest decile was 30 times that of the poorest decile (D10/D1), while in 2000 and 2011 the difference in income between these two groups was 25 and 35.6 times, respectively. This discrepancy occurs since the Gini coefficient is less sensitive to changes in income (Gammage et al., 2014). Moreover, Palma (2011) shows that, historically, improvements in inequality in the Chilean case have been minor and temporary most of the time (on the contrary, deteriorations have been more permanent).[2] Therefore, there is no doubt that income inequality in Chile has been very persistent and its level is still very high.

Given its importance, the literature has paid considerable attention to income inequality in Chile. Nevertheless, all existing studies have used a cross-section distribution of earnings (or wages) to analyze inequality. However, cross-section and lifetime measures of inequality are different because the latter reflects long run resources available to individuals while the former does not. Moreover, cross-section distributions of earnings are just snapshots of the workforce (Gottschalk and Moffitt, 1994). Therefore, using current income to perform inequality studies can be misleading due to the existence of a transitory component in the current income (Blundell and Preston, 1998; Krueger and Perri, 2006). This emphasizes the dynamic dimension of inequality. Along these lines, Flabbi and Leonardi (2010) indicate that earnings inequality is not simply described by the current earnings but also by mobility across jobs and labor market states. Therefore, lifetime inequality measures should take into account labor market states and lifetime wage profiles. Buchinsky and Hunt (1999) and Bowlus and Robin (2004) complement this idea and suggest that individual welfare not only depends on the current employment position but also on the expected evolution of this position over time. Given this discussion, the question that arises is whether the Chilean economy shows a distribution of lifetime earnings that is as highly unequal as its cross-section counterpart.

Many studies have analyzed and compared economies using this lifetime perspective, but they all focus on the United States, Canada or Europe. In the case of emerging economies, the literature is scarce, perhaps because of data limitations. These economies also have the uniqueness that, in general, they have relatively more regulated labor markets and high cross-sectional measures of inequality as can be seen in Fig. 1. This paper seeks to fill this gap by analyzing income inequality from a lifetime perspective in the Chilean economy, thereby improving the standard empirical measures of inequality for Chile. When analyzing income inequality in Chile, the focus is on the labor market because labor income is an important part of earnings (it represents more than 80% of household income, Bravo and Marinovic, 1997), mobility in this market is relatively low,[3] and labor income is very persistent (Huneeus and Repetto, 2005). Therefore, total household inequality is driven mainly by the wages distribution (according to Fig. 2, 90% of the Chilean Gini coefficient is explained by labor income). Additionally, I narrowed the sample to

Fig. 1. Cross-section inequality and labor market structure.

only male workers because this group has a high participation rate and tend to have full time jobs (Ruiz-Tagle, 2007).[4]

This paper uses a search-theoretic framework to analyze long run inequality through the lens of the labor market. In particular, a structural search model with on-the-job search is estimated using the Social Protection Survey dataset for Chile and simulations of careers are used to construct lifetime measures of inequality. The lifetime welfare is then measured as the sum of the discounted values of the simulated labor incomes (Flabbi and Leonardi, 2010; Flinn, 2002). The estimation controls for (observed) heterogeneity in education assuming segmented markets for skilled and unskilled workers. As is usual in the estimation of this type of models, two issues emerge: the first is the right censoring problem and the second is the so called Initial Conditions Problem (Flinn, 2002); the estimation controls for both problems. Finally, the model is used to quantitatively evaluate the mobility and distribution effects on inequality by calculating the marginal effects of the model parameters on lifetime inequality.

The results indicate that inequality is not only high in a cross-sectional perspective, but also in a lifetime perspective and that the regulation of the labor market, reflected in the estimated parameters of the model, matters and has an impact on the degree of mobility in the labor market. This, in turn, has an impact on lifetime measures of inequality: a more flexible labor market generates a less unequal lifetime earnings distribution. This holds regardless of the skill level.

The paper is organized as follows. Section 2 briefly summarizes the related literature. Section 3 presents the model and its equilibrium. Section 4 describes the data and presents the likelihood function. Section 5 discusses the results of the estimation, the lifetime inequality measures and the marginal effect of the estimated parameters in the lifetime inequality measure. Finally, Section 6 concludes.

2. Related literature

This paper is closely related to the literature on structural estimation of partial equilibrium search models. The two closest articles are Flinn and Heckman (1982) and Flinn (2002). The former was the first to present a method to estimate this type of model and the latter extends that procedure to estimate models with on-the-job search.

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[2] In addition, López et al. (2013) analyze data from the Internal Tax Service and show that the inequality measures based on household surveys (as those discussed above) tend to underestimate the level of income concentration. This occurs because of the lack of information on the "very wealthy" in household surveys.

[3] According to the data used for estimation, during the 2002-2005 three-year window, only 12% of all transitions in the Chilean labor market were job-to-job. According to Table 1 in Jolivet et al. (2006), this level of transitions would categorize Chile as a country with low job turnover (the window period was chosen for comparison purposes).

[4] Participation rates for female workers are particularly low in Chile. According to OECD statistics, the average participation rates in Chile in the 2000s were 77.6 and 42% for men and women, respectively. Comparatively, the average participation rates for the OECD countries were 80% for men and 60.2% for women in the 2000s.
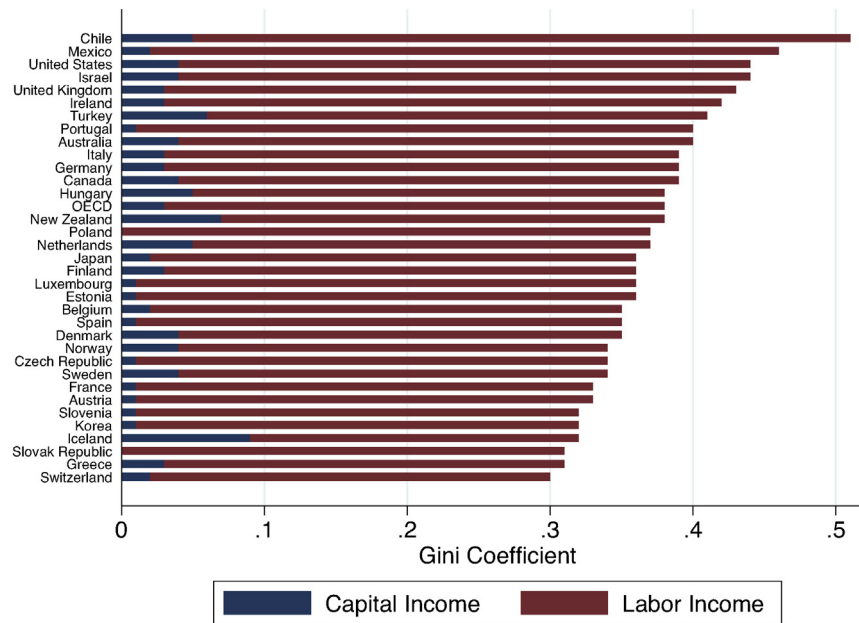
Fig. 2. Contributions to the inequality index of market income — working age population in the late 2000s. Note: Contributions to overall household market income inequality are derived by multiplying the concentration coefficients of each income source by their weight in total market income. The data for Greece, Hungary, Mexico and Turkey are net of taxes. Data for France and Ireland refer to the mid-2000s.
Source: OECD Income Distribution and Poverty, OECD Social Expenditure Statistics (database). Borrowed from OECD's *Economic Policy Reforms: Going for Growth 2012.*

The second group of related literature analyzes long-run welfare inequality and has two streams. The first is the study of income or earnings dynamics, in which some ARMA-type processes (or more complicated processes) are fitted to longitudinal earnings data to decompose earnings in its transitory and permanent components. Some examples are: Gottschalk and Moffitt (1994) and Moffitt and Gottschalk (2002) for the United States; Gangl (2005) who compares Europe and the United States; Chen (2009) who uses data for Canada, the United States, United Kingdom and Germany; Bonhomme and Robin (2009) who use data on France, and Lilla and Staffolani (2009) for the Italian labor market. As mentioned in the previous section, this literature is highly concentrated on the United States, United Kingdom, Canada and European Countries. In the case of Chile there is one paper, that is closest in spirit to this paper: Huneeus and Repetto (2005), who analyze the dynamics of earnings in the life cycle (in line with, for example, Low et al., 2010). They find that earnings are highly persistent, implying little mobility of individuals across the distribution.

The second stream, which is the closest in terms of the approach used in this paper, is based on the search-theoretic framework and analyzes long-run inequality through the lens of the labor market (estimating a structural search model). This literature started with Flinn (2002) comparing the United States and Italy and continued with Bowlus and Robin (2004), who estimate a non-stationary search model for the United States; Flabbi and Mabli (2010), who estimate a model of household search for the United States; and finally, Flabbi and Leonardi (2010), who compare earnings distribution across time in the United States. It is important to mention that Postel-Vinay and Turon (2010) provide a link between these two streams of literature analyzing the relationship between the dynamics of the labor market with search frictions and the dynamics of the earning process.

Finally, the third group of related literature analyzes inequality in Chile. The literature in this area is vast but practically all of the papers have used cross-section distribution of earnings to analyze inequality. Some examples are: Beyer (1995), Beyer (1997), Contreras (1996), Cowan and De Gregorio (1996), Contreras (2002), Bravo and Marinovic (1997), Chumacero and Paredes (2005) and Larrañaga (2009). The main conclusions of this literature are threefold:

first, Chile is one of the countries with the highest cross-section income inequality worldwide; second, cross-section income inequality has been high and persistent across time (particularly in the nineties); and finally, the main factor in explaining between group cross-section income inequality is education.[5] Recently, Sapelli (2011) found that even though wage inequality has been high and persistent overall, positive changes have been observed for young individuals.

3. The model

This section briefly describes the model setup and its solution. The model used in this paper to simulate the dynamics of the Chilean labor market is a standard partial equilibrium random search model with on-the-job search in line with Flinn (2002). It is assumed that the environment is stationary and the economy is populated by a continuum of infinitely lived risk neutral[6] homogeneous agents. At each point in time agents can be unemployed and searching for a job[7] or employed but looking for new job opportunities.

While unemployed, agents receive an instantaneous utility, or possibly a disutility, b (interpreted as the value of leisure), and job offers that arrive according to a Poisson process with parameter λ_U. Job offers take the form of a wage (w) drawn from an exogenous distribution $G(w)$[8]. While employed, agents receive an instantaneous utility (and wage) w. Each job can be terminated with an acceptable new offer or with the arrival of an involuntary separation shock leading to the unemployment state. In the case of the former, job offers while employed arrive according to a Poisson process with

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[5] Beyer and LeFoulon (2002) mention that, even though returns to schooling increases with years of education, the relationship is nonlinear and the wage gap between more and less educated workers has widened. Therefore, segmentation and exclusion may be among the determinants of wage inequality in Chile.
[6] This means that the instantaneous utility flow enjoyed from a flow of income y is $U(y) = y$.
[7] Participation decisions are not modeled in this paper.
[8] The behavior of firms is not explicitly modeled and it is assumed that it is summarized in the wages distribution.

parameter λ_E and, as previously mentioned, they are represented by a wage rate (w) drawn from the distribution $G(w)$. In the case of the latter, this paper departs from the literature assuming that the involuntary separations arrive according to a Poisson process with parameter $\eta(w)$ that depends on the wage level. This assumption is made for two reasons. First, it generates a non constant transition rate to unemployment, avoiding one of the empirically questionable implications of the on-the-job search model pointed out by Flinn (2011)[9]. Second, it limits the level of wage compression in the model. In particular, if the involuntary separation shock arrives at a constant rate, then it is more likely for high wage jobs to be lost (compared to the loss of low wage jobs) with the dynamic process implicit in the model. These high wage jobs are precisely those that are relatively more likely to push to a less compressed wage distribution with a wage improvement. Finally, it is assumed that workers discount the future at an exogenous and constant rate $\rho > 0$ and seek to maximize the expected discounted sum of future utility flows.

Denote the value of unemployment by U and the value of employment for a worker whose wage is w by $W(w)$. As discussed in detail in Flinn (2002), the optimal decision rules in this model have a reservation value property and depend on the type of transition. If the agent receives an offer while unemployed, he/she will accept the offer if the wage is greater than the reservation wage (w^*), which satisfies $W(w^*) = U$. However, if the agent receives an offer while on the job, the outside option corresponds to the current wage which means that the agent will accept the offer only if the new wage (say w') is greater than the current wage (w)[10]. Eq. (1) summarizes the optimal decision rules previously described:

$$d_U(w) = \begin{cases} \text{Accept offer} & w \Longleftrightarrow w \geq w^* \\ \text{Unemployment state} \Longleftrightarrow & w < w^* \end{cases} \quad (1)$$

$$d_E(w) = \begin{cases} \text{Accept new offer} & w' \Longleftrightarrow w' \geq w \\ \text{Continue in current job} \Longleftrightarrow & w' < w \end{cases}$$

Using the values of unemployment and employment, the decision rules and the parameters, it is possible to write the flow value of unemployment as:

$$\rho U = b + \lambda_U \int_{w^*}^{\infty} [W(w) - U] \, dG(w) \quad (2)$$

Eq. (2) indicates that unemployed agents receive a flow utility b and that at rate λ_U they receive a job offer, which if taken ($w \geq w^*$) generates a capital gain of $W(w) - U$. In turn, the flow value of taking a job with current wage w can then be written as:

$$\rho W(w) = w + \lambda_E \int_{w}^{\infty} [W(w') - W(w)] \, dG(w') + \eta(w)[U - W(w)] \quad (3)$$

According to Eq. (3), an employed agent receives a wage rate w and new offers and terminations shocks arrive at rates λ_E and $\eta(w)$, respectively. In the case of a new offer, if it is good enough, meaning that $w' \geq w$, then the worker changes his/her job and obtains a capital gain of $W(w') - W(w)$. Finally, the capital loss will also be $U - W(w)$ when there is an involuntary separation.

By combining Eqs. (2) and (3) with the equilibrium conditions $W(w^*) = U$ and $W(w) = W(w')$ that generate the decision rules in Eq. (1) it is possible to write[11]:

$$w^* = \gamma(w^*)b + [\gamma(w^*)\lambda_U - \lambda_E] \int_{w^*}^{\infty} W(w') \, dG(w') \quad (4)$$

$$W(w) = \theta(w) \left\{ w + \eta(w)W(w^*) + \lambda_E \int_{w}^{\infty} W(w') \, dG(w') \right\} \quad (5)$$

where $\gamma(w^*) = \frac{\rho + \lambda_E \tilde{G}(w^*)}{\rho + \lambda_U \tilde{G}(w^*)}$ and $\theta(w) = \frac{1}{\rho + \eta(w) + \lambda_E \tilde{G}(w)}$

The first equation solves for the reservation wage w^*, while the second solves for the function $W(w)$[12]. Once both are known, the solution of the model is fully characterized and can be used to simulate labor market careers for a given set of parameters and assumptions regarding the parametric form of the wages distribution.

4. Estimation procedure

The model is estimated using Maximum Likelihood Methods with supply side data for the Chilean labor market. This section describes the data available for estimation and briefly discuses the likelihood function, the identification strategy and the potential econometric issues faced in estimation.

4.1. Data

Estimating job search models with on-the-job search requires a rich environment of information because not only are unemployment to employment transitions needed but so are job to job transitions. In other words, information about labor market histories or working cycles is required (Eckstein and van den Berg, 2007). This feature of the data is hard to find for developing economies which, in part, explains why the literature focuses only on the United States, Canada and Europe. This paper uses the Chilean *Social Protection Survey* (Encuesta de Protección Social or EPS), from the Subsecretaría de Previsión Social of the Chilean government[13], which was designed precisely to build a panel of labor market histories. The time span used corresponds to all labor market events that occurred between 2002 and 2007. A detailed explanation of the survey and the construction of the labor market histories is presented in Appendix B.

The model assumes that individuals are homogeneous, making it necessary to apply some sample restrictions in order to guarantee a certain degree of homogeneity consistent with the model. In particular, the estimation sample satisfies the following criteria: males between 20 and 65 years old who are actively participating in the labor market. These sample decisions are important because the model presented does not explicitly model participation decisions, and there is a strong selection problem due to participation decisions in the case of women. Additionally, and given the important role of education in explaining wage inequality in Chile (Contreras, 2002), the sample is divided into two subsamples by education level: skilled and unskilled workers. The former group consists of individuals who have completed tertiary education (that is, more than 14 years of schooling), while the latter group include those who did not

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[9] In fact, as discussed in Section 4, one of the features of the Chilean labor market is that employment to unemployment transitions tend to decrease with wages.
[10] To account for job-to-job transitions with wage cuts, which conditional on Flinn (2002) model are probability zero events, the literature typically uses measurement error in wages for the estimations (Eckstein and van den Berg, 2007).

[11] Appendix A presents the detailed derivation of the equations of the model and the computational algorithm used to solve Eqs. (4) and (5).
[12] It is not difficult to show that Blackwell's sufficient conditions hold. Hence, there is a unique fixed point for w^* and $W(w)$.
[13] The survey is conducted by the Microdata Center of the Economics Department at the University of Chile with the participation of academics of the University of Pennsylvania and the University of Michigan.
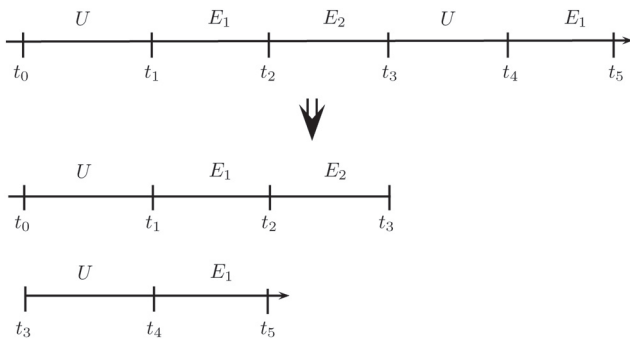
Fig. 3. An example of an individual labor market history that becomes two cycles.

complete that level of education. Initially, there were 2892 individuals in the sample with these characteristics, 688 skilled workers and 2207 unskilled workers.

The sample size is reduced due to other problems with the data. First, there are double censored spells that are in the unemployment state and cannot be used because they generate an identification problem as discussed in the next section (fortunately, this reduction only represents 1.9% of the valid sample). Second, to avoid an outlier problem, due to the existence of unrealistically high wages, 5 of the upper and lower percentiles in wages are dropped from the sample (resulting in a reduction of 15% of the valid sample observations). This is done to make the average wage in the sample comparable with other sources of information, as well as with the literature.[14] It is important to mention that trimming the sample can potentially introduce a selection problem in the sample. However, this is not the case since dropping the observations barely affected the employment rate. Appendix B presents a detailed explanation of the trimming process of the wages data.

The final sample is then organized in working cycles. Each cycle starts in the unemployment state which is followed by all observed job to job transitions (note that it is possible to observe more than one cycle per individual). Working cycles starts in this state because it resets the dynamics of the model (Flabbi and Leonardi, 2010)[15]. If in the case of an individual, the first event observed in January 2002 corresponds to an employment state, then all transitions are also stored for estimation purposes. However, information differentiating both types of cycles, either starting in unemployment or starting in employment, is stored and exploited in the estimation. Fig. 3 shows how the cycle is constructed for a hypothetical example of labor market history. After all data manipulations, the estimation has a total of 693 and 2572 cycles for skilled and unskilled workers, respectively.

It is useful to summarize the information available for estimation and to define the notation used in the likelihood function in the following way:

$$\{t_k(i), w_k(i), c_k(i), r_k(i), \chi(i)\}_{i=1}^{N^C}$$

where: N^C represents the number of cycles observed in the sample, $t_k(i)$, for $k = u, 1, 2, 3$, corresponds to duration information, measured in months, for the kth state in the cycle. Note that $t_1(i)$ represents the duration of the first job after the unemployment state and the first

observed job when the cycle starts in an employment state. On the other hand, $w_k(i)$, for $k = u, 1, 2, 3$, is the wage measured in 2004 U.S. dollars per hour for the kth state in the cycle. Note that $w_u(i)$ corresponds to the first accepted wage out of the unemployment state while $w_1(i)$ corresponds to the wage observed in a cycle that starts in an employment state.[16] Left censored spells are represented by $c_k(i)$, for $k = u, 1, 2, 3$, which are dummy variables that take the value 1 if the spell is censored and zero otherwise. Terminations in unemployment are indicated by $r_k(i)$, for $k = 1, 2, 3$, which are dummy variables that take the value 1 if a transition between employment and unemployment is observed and zero otherwise. This also implies that the cycle is complete. Finally, χ indicates whether the cycle starts in a unemployment state. It is a dummy variable that takes the value 1 if the unemployment state is observed at the beginning of each cycle and zero otherwise.

Tables 1 and 2 present descriptive statistics on duration and hourly wages in each state of the cycle, differentiating by the nature of the first event of the cycle (unemployment state or employment state) and by level of education. With respect to the duration information, Table 1 indicates that while skilled workers remain unemployed for two more months than unskilled workers on average, they keep their jobs for longer periods compared to the unskilled workers. This is true when the cycle starts in an unemployment spell. On the other hand, when the cycle starts in an employment spell, such differences in the average job duration are not that evident, at least in the case of the first observed job. When the cycle starts in an unemployment spell, the right censoring problem is important because more than 20% of the spells in the unemployment state and in the first job are censored. When the cycle starts in employment this problem becomes even more evident. Hence it is important that the estimation method controls for this problem in order to avoid censoring bias. The left censored problem does not represent an issue because less than 2% of the spells have unknown starting dates.

Wages information, in Table 2, shows that skilled workers earn, on average, twice that earned by an unskilled worker in the first job after being unemployed. This gap widens the other job in the cycle. While more than 40% of the wages fall in the transition from the first job, after unemployment, to the second job, the decrease is more than 80% in the transition to the third job. However, this drop in wages should not be large in magnitude because the average wage increases in each of these transitions. When the cycles start in an employment state the gaps between wages of skilled and unskilled workers are similar to those observed when the cycle starts in an unemployment state. In terms of wage cuts, however, the story is different. Even though in the transition of the first to the second job only 10% of the wages fall, the average wage experiences a reduction. This means that the magnitudes of the wage reductions are large. In the transition to the third job, almost 75% of the wages fall and as a result the average wage also falls. Finally, it is evident that the distribution of wages is more disperse for skilled workers.

Table 3 shows transition rates to unemployment for all complete cycles, differentiating by wage and skill levels. There are three important features that support to the assumption of non constant arrival rate of involuntary separation shocks. First, they decrease as wages increase, this holds for both skilled and unskilled workers. Second, even though there is a higher proportion of low-wage skilled workers (compared to unskilled workers) who transit to unemployment, the transition rate decrease of the unskilled workers decreases more rapidly. Finally, the relationship between transitions

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[14] In the 2006 National Socio-economic Survey (CASEN) the average wage was US$5.60 and US$1.80 per hour for skilled and unskilled workers, respectively (in US$ of 2004). Also, Fuentes et al. (2005), using the same survey, estimate that in 2003 the average monthly real labor income for males was US$2.28 per hour.

[15] The model ignores returns to experience because any potential gains in wages are lost once the workers go to unemployment. However, this does not represent a potential limitation given that, according to Montenegro (2001) and Sapelli (2006), returns to experience in Chile during the 2000s were low (on average 1%).

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[16] I use Flabbi and Leonardi (2010) notation to differentiate the cycles that start in unemployment from the cycles that start in employment because the first observed wage in a cycle starting in employment does not necessarily coincide with the first wage out of unemployment.

Table 1
Descriptive statistics on durations (months).

Event	Skilled			Unskilled		
	Mean	S.D.	% of RC	Mean	S.D.	% of RC
All cycles						
t_u	10.72	22.54	0.04	8.33	20.99	0.06
t_1	114.84	73.91	0.67	100.41	78.61	0.55
t_2	18.01	13.22	0.12	15.62	12.14	0.12
Cycles starting in unemployment state						
t_u	10.72	22.54	0.27	8.33	20.99	0.23
t_1	12.22	13.42	0.35	9.65	11.26	0.29
t_2	12.63	8.78	0.13	12.41	11.18	0.09
Cycles starting in employment state						
t_1	127.88	68.00	0.73	127.45	69.25	0.65
t_2	19.05	13.70	0.12	16.70	12.27	0.13

Note: t_u represents the duration of the unemployment spells and t_i with $i = 1, 2$ represent the duration of the first and second job spells in the cycle, respectively. Left censored spells are 0.6% and 1.6% of the total spells for skilled and unskilled workers, respectively.

Table 2
Descriptive statistics on wages (US$ of 2004).

Event	Skilled			Unskilled		
	Mean	S.D.	$\% w_{t+1} > w_t$	Mean	S.D.	$\% w_{t+1} > w_t$
All cycles						
w_u/w_1	5.18	3.77	0.85	1.94	0.94	0.82
w_2	4.21	2.95	0.16	1.73	0.75	0.18
w_3	4.38	2.90		1.81	0.86	
Cycles starting in unemployment state						
w_u	3.34	2.89	0.66	1.45	0.60	0.69
w_2	4.17	2.72	0.18	1.54	0.54	0.17
w_3	6.08	4.02		1.65	0.70	
Cycles starting in employment state						
w_1	5.42	3.80	0.89	2.08	0.98	0.87
w_2	4.22	3.00	0.16	1.80	0.79	0.18
w_3	4.04	2.55		1.87	0.90	

Notes: On one hand, w_u represents the wage rate of the first job after unemployment, while w_1 is the wage rate of the first observed job (when the cycle starts in employment). On the other hand, w_i with $i = 2, 3$ represent the wage rate in the second and the third jobs (regardless of whether the cycle started in an unemployment spell or not). The figures, expressed in US$ of 2004, were calculated using the 2004 average exchange rate: 609.55 $Pesos/US$.

to unemployment and wages does not seem to be linear and is highly heterogeneous by skill level.

4.2. The likelihood function

The estimation procedure used in this paper, as well as its description, closely follows Flabbi and Leonardi (2010). However, before presenting the likelihood function, it is important to discuss the fundamental problem faced when estimating search models with on-the-job search and working cycles that start in an employment state are present: the initial condition problem[17]. Note from the model in Section 3 that an individual who starts in an unemployment state draws an acceptable wage from a distribution truncated at w^*, that is: $\frac{\int_{w^*}^{\infty} g(w)}{1-G(w^*)}$. On the other hand, when on the job the worker draws an acceptable wage from a distribution truncated at its current wage w_k with $k = u, 2, 3, \ldots$, that is $\frac{\int_{w_k}^{\infty} g(w)}{1-G(w_k)}$. Since, by construction, $w_3 \geq w_2 \geq w_u$, the distribution of the kth job stochastically

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[17] In this paper the discussion is rather brief and informal. For a formal exposition of the problem see Flinn (2002).

Table 3
Percentage of employment to unemployment transitions by wage.

Wage group (U.S dollar/hour)	Percentage of $e - u$ transitions
Unskilled workers	
<1	34.7
1–2	22.2
2–3	19.0
3–4	12.5
4–5	0
>5	0
Skilled workers	
<3	40.0
3–6	39.1
6–9	36.0
9–12	34.1
12–15	28.6
>15	0.4

Note: The second column corresponds to the percentage of employment to unemployment transitions with respect to all observed transitions by different wages groups and skill level.

dominates (at least weakly) the distribution of the $k^{th} - 1$ job. Therefore, order matters. Now lets consider a worker who is observed for the first time in an employment state. Without any information on the previous states in the labor market it is impossible to know the order of the job, and hence the distribution that generates the wage. This has implications for the contribution of wages to the likelihood function because those contributions are precisely related with that unknown distribution.

The literature proposes various procedures to address this problem. One option, described in Flinn (2002), is to find the steady state distribution of wages and assume that the system has reached that state. Another alternative, proposed by Ridder and van den Berg (2003) and used to estimate the arrival rates, uses only data on duration and the wage distribution of the workers initially observed after unemployment. Barlevy and Nagaraja (2010) go further and propose a method, suitable under some particular assumptions, to estimate these rates using only duration data and completely ignoring wage information (in particular, it exploits heterogeneity in the hazard rates). A third option, used by Flinn (2002) and Flabbi and Leonardi (2010), is to write the likelihood conditioning on the wage of the first job observed at the beginning of the sample (that is, the first job of the cycles that starts in employment). Even though this last procedure generates consistent estimates at the cost of losing some information, it is the most suitable for the particular application of this paper.

With respect to the first option, since more than a third of the sample used in the estimations corresponds to young workers (i.e., those younger than 35 years), it is potentially inappropriate to make the assumption that this group of workers has already reached its steady state distribution of wages. Furthermore, since the analysis of lifetime inequality requires both the transitions across the state and the wages distribution the second group of approaches provides only partial information.

In the construction of the likelihood function it is necessary to define the contributions of the data in each state. The hazard rate in all states (that is, the probability of termination of the state conditional on its survival up to this point) must first be defined in order to describe the contribution of the duration data. On one hand, conditional on the model, when the individual is unemployed the hazard rate is:

$$h_u = \lambda_u (1 - G(w^*))$$

that is, the probability that an acceptable offer arrives. On the other hand, conditional on the model, when the individual is employed the hazard rate is:

$$h_e(w) = \lambda_E(1 - G(w)) + \eta(w)$$

or the probability of termination of the current job due to the arrival of an acceptable offer or an involuntary separation shock. With respecto to $\eta(w)$, it is assumed that the relation between the arrival rate of the involuntary separation shock and wages is deterministic and characterized by a Poisson regression with a polynomial in wages. That is,

$$\ln \eta(w) = \sum_{i=0}^{K} \eta_i w^i$$

On one hand, the assumption of a deterministic relation in $\eta(w)$ produces a result consistent with the empirical observation of a non constant relation between transitions to unemployment and wages, while maintaining the main implication of the model -the occurrence of job-to-job transitions only after wage increases (Flinn, 2011). On the other hand, the polynomial in wages is used to allow flexibility in the form of the function (i.e. to capture non linearities) and its degree is chosen using model fit considerations. Note that both λ_E and $\eta(w)$ are constant with respect to the duration, implying that the density of a complete spell in each state can be characterized by a negative exponential distribution with a parameter equal to the hazard rate[18].

To express the contribution of the durations of unemployment and employment states to the likelihood function it is important to be aware that the data can be right censored, that is the termination of a particular state is at a later date than the last observed date[19]. In the unemployment state, and given the hazard rate h_u, the contribution of the unemployment duration to the likelihood function for a complete spell and for a right censored spell, respectively, is defined as follows:

$$f_u(t_u) = h_u \exp(-h_u t_u) \tag{6}$$

$$f_u(t_u, c_u^r = 1) = \Pr[T > t_u] = \exp(-h_u t_u) \tag{7}$$

On the other hand, given the hazard rate $h_e(w)$, the contributions of the employment duration to the likelihood function when the spells are complete can be expressed as follows depending on the condition of termination of this state:

$$f_e(t_k, r_k = 1 | w_k) = h_e(w_k) \exp(-h_e(w_k)t_k) \frac{\eta(w_k)}{h_e(w_k)} \tag{8}$$

$$f_e(t_k, r_k = 0 | w_k) = h_e(w_k) \exp(-h_e(w_k)t_k) \frac{\lambda_E(1 - G(w_k))}{h_e(w_k)} \tag{9}$$

In Eq. (8) the density of duration is adjusted by the probability of transition to unemployment conditional on leaving a job with wage w_K. In Eq. (9) the adjustment is made with the probability of

transitioning to a new job, conditional on leaving a job with wage w_K. It is important to note that each contribution in Eqs. (8) to (9) is conditional on the wage of the current spell. Finally, with right-censored spells we have the following contribution of the employment duration to the likelihood function (in this case, the condition of termination is unknown):

$$f_e(t_k, c_k^r = 1 | w_k) = \exp(-h_e(w_k)t_k) \tag{10}$$

To define the contribution of wages to the likelihood function it is important to consider that accepted wages are observed in the data. Conditional on the model, that is using the decision rules inEq.(1), it is possible to write the contributions of accepted wages in each state of the cycle as:

$$f_w(w_u) = \frac{g(w_u)}{1 - G(w^*)} \tag{11}$$

$$f_w(w_{k+1} | w_k) = \frac{g(w_{k+1})}{1 - G(w_k)} \tag{12}$$

where $g(\cdot)$ and $G(\cdot)$ are the p.d.f. and c.d.f. functions, respectively. Eqs. (11) and (12) are simply the densities of acceptable offers when leaving the unemployment state (truncated at the reservation wage w^*) and the current job (truncated at the current wage w_k), respectively.

Given the self-reported and retrospective nature of the data, it is highly likely that wages are measured with error[20]. If wages are measured with error, the observed wage is $w^o = w\varepsilon$ where the measurement error ε has a c.d.f. $Q(\varepsilon)$ and p.d.f. $q(\varepsilon)$ (see, for example, van den Berg and Ridder, 1998, Wolpin, 1987). The c.d.f. of the observed wage is, therefore, $Q\left(\frac{w^o}{w}\right)$ which means that the density of the observed wages takes the form of $\frac{1}{w}q\left(\frac{w^o}{w}\right)$. As is standard in the literature, measurement error also makes it possible to empirically account for job to job transitions with wage cuts.

The density of the observed wages can now be expressed by integrating the support of the (true) accepted wages:

$$f_w(w_u^o) = \int_{w^*} \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) dw_u$$

$$f_w(w_{k+1}^o | w_k) = \int_{w_k} \frac{1}{w_{k+1}} q\left(\frac{w_{k+1}^o}{w_{k+1}}\right) f_w(w_{k+1} | w_k) dw_{k+1}$$

Due to space considerations the full likelihood function, using all the elements presented in this subsection, is presented in Appendix C[21]. However, two examples are presented in this section. First, the individual likelihood function of a cycle that starts in unemployment and has no right censored duration in unemployment but has right censored duration in the first job is defined as:

$$L(\chi = 1, c_u = 0, c_1 = 1)$$
$$= f_u(t_u) \int_{w^*} f_e(t_1, c_1 = 1 | w_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) dw_u$$

The second example is related with the individual likelihood function of a cycle that starts in unemployment, has no right censored duration in the unemployment spell as well as in the first and

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[18] That is $f(t) = h\exp(-ht)$ for $t > 0$.

[19] The estimation does not correct for left censored spells because they represent only a small number of observations (see Table 2). On the other hand, cycles with double censored spells are ignored because of an identification problem. As noted by (Flinn, 2002), when there are events in which an individual is continuously unemployed, the parameters of the model are not identified since permanent unemployment can be produced by $\lambda_U = 0$, $\eta(w) = 1$ for all w, $b = 1$ or by any combination of these conditions. Fortunately these observations consisted only of 1.9% of the sample.

[20] As is common in the literature, it is assumed that measurement error is present in wage data but not in duration data (Eckstein and van den Berg, 2007; Flinn, 2006).

[21] As in Flinn (2002) and Flabbi and Leonardi (2010) only two consecutive jobs are used as a job to job transition because when the number of transitions grows the likelihood function becomes rapidly intractable.

Table 4
Maximum likelihood estimates.

Parameter	Skilled workers	Unskilled workers
λ_U	0.06800	0.09279
	(0.00785)	(0.00395)
λ_E	0.01142	0.00734
	(0.00111)	(0.00034)
η_0	−4.84714	−10.03166
	(0.59698)	(0.52549)
η_1	−0.34810	4.12087
	(0.11486)	(0.46588)
η_2	0.00426	−0.80555
	(0.00184)	(0.08053)
μ	1.51178	0.53604
	(0.05154)	(0.01683)
σ	0.09417	0.26753
	(0.00797)	(0.00798)
w^*	3.37998	0.66110
	(0.23439)	(0.02390)
μ_ϵ	−0.27929	−0.12267
	(0.02254)	(0.00591)
b	2.50070	−0.58210
$E(w)$	4.55495	1.77150
$V(w)$	0.18481	0.23284
$\eta(E(w))$	0.00176	0.00520
$LogL$	−2513	−11330
N	693	2572

Note: Asymptotic standard errors in parentheses.

second jobs, and terminates in unemployment after the second job (complete cycle):

$$L(\chi = 1, c_u = 0, c_1 = 0, r_1 = 0, c_2 = 0, r_2 = 1)$$
$$= f_u(t_u) \int_{w^*} f_e(t_1, r_1 = 0 | w_u) \frac{1}{w_u} q\left(\frac{w_u^0}{w_u}\right) f_w(w_u)$$
$$\times \int_{w_2} f_e(t_2, r_2 = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2 | w_u) dw_2 dw_u$$

Two standard assumptions are made in the estimation. First, $G(\cdot)$ is a lognormal probability distribution function with parameters (μ, σ), and second, $Q(\cdot)$ is a lognormal probability distribution function with parameters $\left(\mu_\epsilon, \sqrt{-2\mu_\epsilon}\right)$[22]. Finally, it is important to mention that all the parameters in the model are identified[23]. The identification strategy relies on, and is extensively discussed in, Flinn and Heckman (1982) (recoverability conditions and unemployment-employment transitions) and Flinn (2002) (job-to-job transitions).

5. Results

5.1. Estimation results

Table 4 presents the maximum likelihood estimates of the model parameters (λ_U, λ_E, η_0, η_1, η_2, μ, σ, μ_ϵ, b) and the reservation wage w^* for both skilled and unskilled workers. In the estimation, a polynomial of degree 2 for the function $\eta(w)$ is the specification that best fits the data for both types of workers (that is, it is the specification with the highest value of the log-likelihood function).

On one hand, the estimates of the arrival rates of job offers while unemployed λ_U imply that skilled and unskilled workers should, on average, expect offers every 15 and 11 months, respectively. This implies that it takes time to leave the unemployment state. This result is qualitatively different from the findings of Flabbi and Leonardi (2010) for the U.S. economy and could indicate that in Chile the labor market is tighter for skilled workers. On the other hand, the arrival

rate of offers while on the job, λ_E, indicate that new job opportunities do not arrive often in the Chilean labor market. In particular, skilled and unskilled employees should, on average, expect the arrival of new job opportunities every 7 and 11 years, respectively. Therefore, compared with skilled workers, the unskilled workers are less fortunate in receiving job offers while on the job. Estimates of the arrival rates of involuntary separations, parameters η_0, η_1 and η_2, in turn, indicates that it is not common to observe terminations due to this type of shock because it takes more than 47 (16) years for skilled (unskilled) workers earning the average wage to receive an involuntary separation shock. The findings for λ_E and η combined indicate that jobs are very persistent in the Chilean labor market. This result is consistent with the findings in Huneeus and Repetto (2005).

The reservation wage in the Chilean labor market for skilled workers is US$3.40 per hour, while for unskilled workers it is US$0.70 per hour. Hence, skilled workers request a wage that is 5 times that requested by unskilled workers in order to accept a job while unemployed. The estimates of the parameters that govern the wage distribution, that is μ and σ, imply an average offered wage of US$4.6 and US$1.8 per hour for skilled and unskilled workers, respectively. Therefore, skilled workers earn, on average, more than twice that earned by unskilled workers. Furthermore, the standard deviation of wages is around US$0.45 per hour with almost no difference across education levels. The values of the estimates for the reservation wage and the parameters of the wages distribution imply that the average accepted wages are on an order of magnitude similar to those of the average offered wages for both types of workers. Finally, it is pertinent to mention the estimates of the measurement error distribution parameters. The distribution of the measurement error is 1.5 times more dispersed for skilled workers (recall that $\sigma_\varepsilon = \sqrt{-2\mu_\varepsilon}$) indicating that larger measurement errors are more likely to occur in the observed wages of this group of workers.

5.2. Cross-section vs. lifetime inequality

In order to generate lifetime inequality indices, it is necessary to first construct measures of long-run welfare. A simulation method is used to achieve that goal. In particular, as in Flinn (2002) the model is simulated to construct labor market careers of 45 years for 10,000 individuals using the point estimated parameters in Table 4. To preserve the relative weights in the composition of the groups with different education levels, 21% of the individuals were simulated using the skilled worker estimated parameters while the remaining individuals were simulated using the estimated parameters of the unskilled workers. In the simulation each individual started its career in the unemployment state[24] and in each period a wage and duration were drawn from the appropriate distributions. In the case of the wage, a lognormal distribution truncated at the reservation wage or at the current wage, depending on the type of transition, was used, while in the case of the duration the relevant distribution was the exponential distribution. Once the careers were simulated, the long-run (or lifetime) welfare for an individual i was calculated as the sum of the discounted value of his labor income in each state, that is[25]:

$$LW_i = \sum_{j=1}^{J} \exp(-\rho t_j) \int_{t_j}^{t_{j+1}} y_{ij} \exp(-\rho v) dv \qquad (13)$$

where $y_{ij} = b$ if the spell j is unemployment, $y_{ij} = w_{ij}$ if the spell j is employment, t_j is the duration of the spell j and J is the total number of spells (note that $\sum_{j=1}^{J} t_j = 540$ months). In Eq. (13) each flow

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[22] This is a consequence of two assumptions (1) $E(\varepsilon | w) = 1$ and (2) lognormality.
[23] Parameters ρ and b cannot be identified separately, but if a value of ρ is assumed then b can be obtained from Eq. (4). In the particular case analyzed, ρ is defined as 0.065 in annual terms (see, for example, Fuenzalida and Mongrut, 2010).

[24] This can be interpreted as an individual looking for a job for the first time.
[25] For the details of the simulation procedure and the calculation of the lifetime welfare see Appendix B in Flinn (2002).

Table 5
Lifetime vs cross-section inequality measures.

	n_s/n	y	GE(0)	GE(1)	GE(2)
Lifetime inequality measures: welfare					
Total	1.0000	389.3852	0.1890	0.2241	0.3411
Skilled	0.2123	767.0747	0.1696	0.1739	0.2156
Unskilled	0.7877	287.5907	0.0739	0.0758	0.0854
Within-group inequality			0.0942	0.1168	0.2143
Between-group inequality			0.0948	0.1073	0.1268
Cross-section inequality measures: simulated earnings					
Total	1.0000	2.4229	0.2933	0.3235	0.5151
Skilled	0.2136	4.7520	0.2889	0.2849	0.3710
Unskilled	0.7864	1.7904	0.1749	0.1684	0.1977
Within-group inequality			0.1992	0.2172	0.3896
Between-group inequality			0.0941	0.1063	0.1255
Cross-section inequality measures: observed earnings					
Total	1.0000	2.8399	0.2253	0.2598	0.3741
Skilled	0.2410	5.3095	0.2308	0.2219	0.2494
Unskilled	0.7590	2.0558	0.0991	0.1009	0.1105
Within-group inequality			0.1308	0.1554	0.2540
Between-group inequality			0.0944	0.1044	0.1201

Note: Observed earnings correspond to those observed in June 2004. Simulations are performed using $b = 0$ for both, skilled and unskilled workers. Simulated earnings are corrected for measurement error to make them comparable with the observed earnings.

income in the career is discounted to the beginning of its corresponding spell; then all these discounted values are again discounted to the beginning of the period[26].

In addition to the construction of the lifetime welfare measures, a distribution of cross-section measure of labor incomes can also be extracted from the simulations. This is particularly useful to asses the fit of the model in matching moments of that distribution with those observed in the data[27]. The cross-section measure of labor incomes is just the average hourly wage in the 11*th* year of the career. As in Flinn (2002) and Flabbi and Leonardi (2010), the Generalized Entropy classes of inequality indices are used to judge the degree of inequality in both the cross-section measure of labor income and the lifetime measure welfare. The Generalized Entropy inequality index with parameter α is defined by[28]:

$$GE(\alpha) = \begin{cases} \frac{1}{\alpha(\alpha-1)}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i}{\bar{y}}\right)^{\alpha} - 1\right] & \alpha \neq 0,1 \\ \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\bar{y}}\ln\left(\frac{y_i}{\bar{y}}\right) & \alpha = 1 \\ -\frac{1}{N}\sum_{i=1}^{N}\ln\left(\frac{y_i}{\bar{y}}\right) & \alpha = 0 \end{cases} \qquad (14)$$

where N is the number of individuals, y_i is the measure of income for individual i and α is a parameter that weights the distance between incomes along the distribution. The larger the parameter α, the greater is the weight of the income differences among the rich. Also, according to the value of the parameter α, several inequality statistics arise. For example, GE(0) is the mean log deviation, GE(1) is the Theil index, and GE(2) is half the coefficient of the variation.

Given the important differences in the labor market dynamics by education level, it is also useful to decompose the inequality indices to see if the overall inequality reflect differences within skill groups or differences between skill groups. The decomposition used is the following (Jenkins and Van Kerm, 2011):

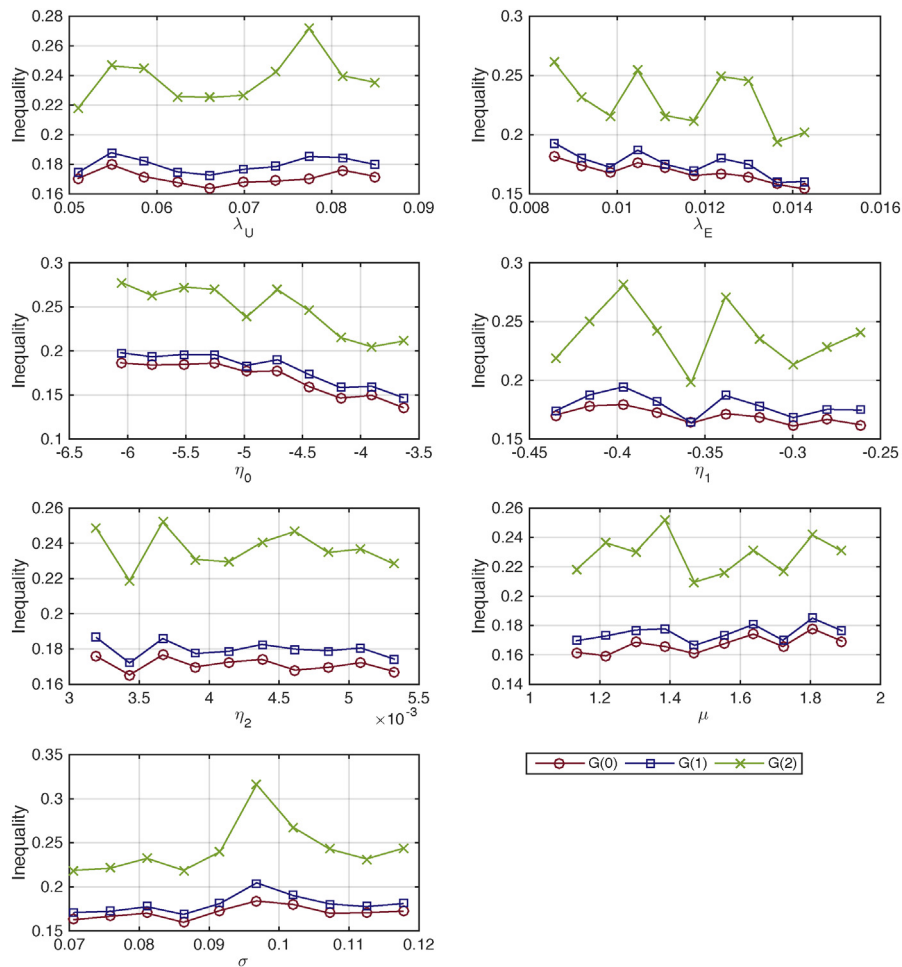$$GE(\alpha) = GE^B(\alpha) + GE^W(\alpha) \qquad (15)$$

The within-group inequality can be calculated for M subgroups as follows:

$$GE^W(\alpha) = \sum_{m=1}^{M} = \theta_m^{\alpha}\psi_m^{1-\alpha}GE_m(\alpha) \qquad (16)$$

where θ_m is subgroup m's share of total income, ψ_m is m's population share, and $GE_m(\alpha)$ is the inequality within group m. Between-group inequality, $GE^B(\alpha)$, can be calculated by imputing the mean income of each subgroup to all the individuals in that subgroup.

Table 5 shows the inequality indices, for $\alpha = 0, 1, 2$, calculated using the lifetime welfare measures (upper panel), the simulated cross-section earnings (middle panel) and a cross-section of earnings extracted from the data (lower panel). In each panel the decomposition described above is also presented by education level. Before discussing the findings in lifetime inequality, it is important to highlight the extent to which the model is able to replicate the data in the cross-section. Comparing the middle with the lower panels of Table 5, it is evident that the model tends to overestimate the level of inequality and this occurs not only with the total sample but also by skill level. The difference also becomes greater when more weight is given to the differences in income shares among the rich (that is α if higher). Hence, the estimates with lower values of α will receive more weight in the conclusions. On the other hand, the model is successful in preserving the inequality ordering observed in the data — inequality tends to be higher for skilled workers and the source of inequality, for both skilled and unskilled workers, lies primarily in the differences in earnings within groups. The model also delivers relatively close estimates of the average earnings for all samples and by skill level.

The estimates of lifetime inequality, in the upper panel of Table 5, indicate that inequality in the Chilean labor market is not only high at the cross-section level but also from a lifetime perspective. Even though these estimates probably are slightly overestimating the true

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[26] As in Flinn (2002) the simulations were performed using the point estimates of all the parameters (in Table 4) except for b which was set to zero. This parameter is imprecisely estimated and since the wages profile in the labor market career is crucial for this paper, setting it to zero limits its influence on the estimates of the lifetime welfare. In any case, the main results are maintained with the estimated value of b.

[27] In order to compare this generated wages distribution with that observed in the data, the former has to be adjusted to include the measurement error. This can be done by generating random numbers from a lognormal distribution using the parameters estimated in Table 4 for the measurement error.

[28] As Cowell (2000) mentions, any measure of inequality should satisfy (1) Anonymity (the metric does not depend on who is the individual), (2) Scale independence (the metric is independent of the aggregate level of income), (3) Population independence (the metric does not depend on the size of the population), and (4) Transfer principle (the metric has to decrease if there are transfers from rich to poor agents). The Generalized Entropy inequality indices satisfy these axioms.

Fig. 4. Effect of individual parameters on lifetime inequality measures − skilled workers. Note: Calculations based on simulations of 2123 individuals, while changing each parameter at a time and maintaining the remaining parameters in their estimated values. All the equilibrium effects are taken into account in each simulation.

level of inequality, given the previous discussion, they are still high (relative to the cross-section measures in the data). The results are reinforced by the fact that these measures of inequality correspond to male workers only (incorporating women probably will make inequality higher). As in the cross-section inequality case, lifetime welfare of skilled workers tends to be more unequal when compared with their unskilled counterparts. Note that the sources of the lifetime inequality are differences in wages between and within skilled groups. The lifetime inequality within groups is driven by the persistence of each of the labor market states, reflected in the estimated values of the arrival rates, because once a worker reaches a given state he/she remains in that state for a long period of time. This is reflected in the fact that the estimated model (for both types of workers) has a low rate of convergence to the steady states. In particular, it takes 7 and 5.5 years for the unemployment rate to reach its steady state in the model in the case of skilled and unskilled workers, respectively. It is important to note that in the simulations, all workers are unemployed in the first spell and become employed in the second spell while in their third spell, they can either be unemployed or employed. If these spells have long durations, and given that wages are constant while the spell lasts, workers do not climb rapidly in the wages distribution. These facts are reinforced by a compressed wages distribution (particularly for skilled workers) which implies that very few workers are lucky enough to have really large wage upgrades when they change jobs. In turn, the lifetime inequality between skilled and unskilled workers is explained by differences in the dynamics of their labor markets as well as in the

wages distribution. In sum, these results are explained by the importance of these first spells (given the discounting), the differences between skilled and unskilled workers, and the fact that labor market states show long spells. This result (and the estimated parameters) contrasts the results found by Flinn (2002) for the United States. Finally, the estimates indicate that an average worker in Chile has a lifetime welfare (in this case, also earnings) of US$389 per hour, with US$767 and US$287 per hour for skilled and unskilled workers, respectively.

5.3. Marginal effect of individual parameters on lifetime inequality

The same simulation approach is used to find the marginal effect of each individual parameter on the lifetime inequality measures[29]. In particular, the model is simulated to create careers changing one parameter in a range of ±25% while keeping the rest of the parameters at their point estimates. This is done by skill level and the inequality indices, $G(\alpha)$ for $\alpha = 0, 1, 2$, are calculated with the resulting welfare measures. For example, to find the marginal effect of λ_U, for the case of skilled workers, simulations are performed using different values of this parameter ranging from 0.050 to 0.085 while maintaining the other parameters in the estimates (second column) of Table 4.

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[29] The results of this subsection should be taken with caution given the partial equilibrium nature of the model used in this paper.
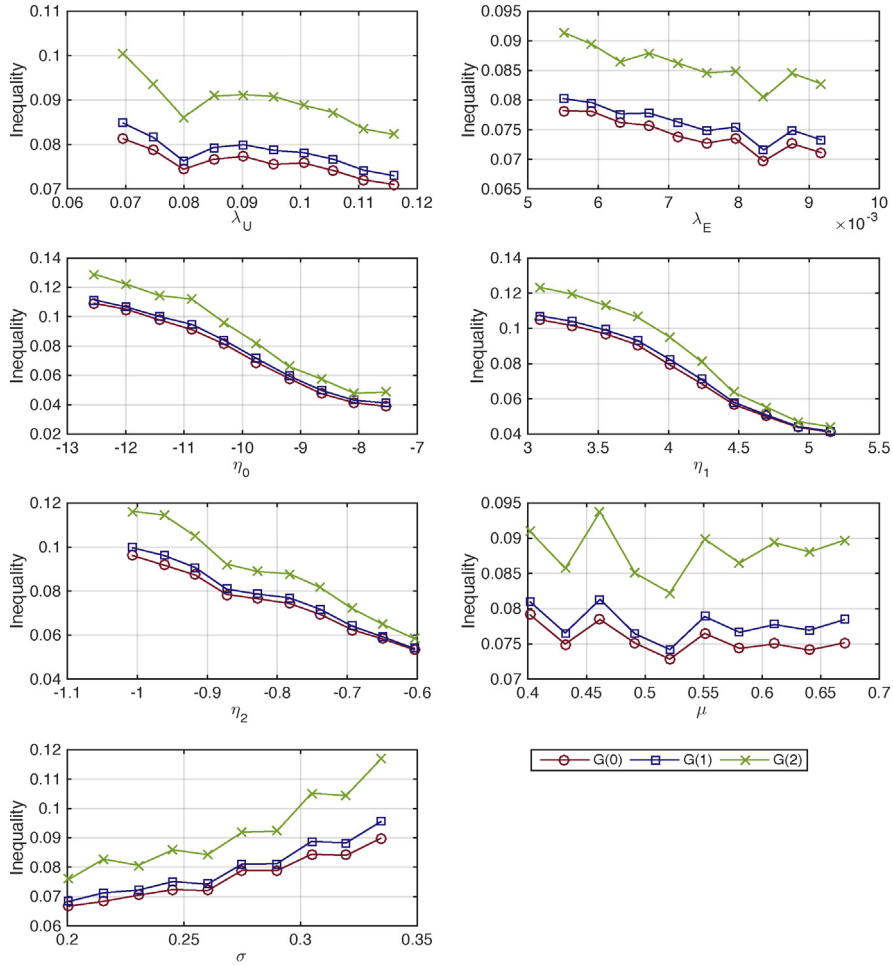
Fig. 5. Effect of individual parameters on lifetime inequality measures — unskilled workers. Note: Calculations based on simulations of 7877 individuals, while changing each parameter at a time and maintaining the remaining parameters in their estimated values. All the equilibrium effects are taken into account in each simulation.

The results are shown in Figs. 4 and 5 for skilled and unskilled workers, respectively. In the case of skilled workers (Fig. 4), it is evident that the parameters with the greatest impact on the lifetime inequality measures are the arrival rates of job opportunities while on the job and the arrival rates of the termination shock at all levels of income (the constant component). The effect of both parameters is in the same direction, that is the faster workers leave their jobs (for another job or to unemployment) the lower is the lifetime inequality, but the size of the impact of the former is smaller. On the contrary, the arrival rate of job offers while unemployed and the sensitivity of the arrival rate of the termination shock to wages does not appear to significantly affect lifetime inequality measures. In terms of the distribution parameters, an increase in the variance of the logarithm of wages tends to increase lifetime inequality. In the case of the mean logarithm of wages, the direction of the effect is not clear.

In the case of unskilled workers (Fig. 5), the results show that lifetime inequality for this group is considerably more sensitive with respect to the mobility parameters than for the skilled workers. In particular, lifetime inequality measures tend to be lower when there is more mobility in the labor market, than when workers rapidly leave both the unemployment and the employment states. Also, the more sensible the arrival rate of the termination shock to wages is, the lower is the lifetime inequality. With respect to the distribution parameters, the results are similar to those found for skilled workers. In particular, while the impact of the mean logarithm of wages is not clear, the variance of the logarithm tends to increase lifetime inequality measures. These findings reinforce the conclusion that

the mobility parameters are one of the main forces behind the high lifetime inequality observed in the Chilean labor market.

6. Concluding remarks

This paper structurally estimates a partial equilibrium search model with on-the-job search using data for the Chilean labor market. The model is estimated separately by education level (skilled vs. unskilled workers). Chile is chosen because it has high and persistent levels of cross-section inequality and it has a rich data set with labor market histories. This is crucial because any attempt to judge lifetime inequality requires both transitions from unemployment to employment and job to job transitions. In order to calculate a long-run measure of welfare, the model and the estimated parameters are used to simulate labor market careers. In particular, the discounted value of the labor income along the career was used as a measure of welfare. Finally, the Generalized Entropy family of indices are used to judge the degree of inequality in this measure of welfare.

The estimation results indicate that there are important differences in the dynamics of the labor market by education level. In terms of the transitions across labor market states, the estimated results show that it takes time to leave the unemployment state and this is more pronounced for the skilled worker. On the other hand, new job opportunities do not arrive often in the Chilean labor market and the unskilled workers are less fortunate in receiving job offers while on the job. In turn, involuntary separations are not common

to observe. It can be inferred from the last two findings that jobs are very persistent in the Chilean labor market. In terms of the wages distribution, the results indicate that skilled workers earn on average more than twice that earned by unskilled workers and that the dispersion in the wage distribution by education level is very similar. Finally, with respect to the reservation wages, it is found that skilled workers request a wage that is 5 times that requested by unskilled workers, in order to accept a job while unemployed.

The estimates of lifetime inequality show that inequality in the Chilean labor market is not only high at the cross-section level but also from a lifetime perspective. Also, as in the cross-section perspective, lifetime welfare for skilled workers tends to be more unequal when compared with their unskilled counterparts. To analyze in more detail the effect of each parameter on the lifetime inequality measures, the marginal effect of each individual parameter is constructed using the same simulation approach. The results indicate that the mobility parameters are the main driving force behind lifetime inequality measures, for both skilled and unskilled workers.

Appendix A. Model solution

This appendix presents the full derivation of the equations of Section 3 and discusses an algorithm to solve the dynamic programming problem. If an infinitesimally small period of time Δt is considered, then the value of unemployment is:

$$U = b\Delta t + \frac{1}{1+\rho\Delta t}\left\{ \begin{array}{c} [\lambda_U\Delta t + \sigma(\Delta t)]\int \max\{U, W(w')\}\,dG(w') \\ + (1 - [\lambda_U\Delta t + \sigma(\Delta t)])\,U \end{array} \right\}$$

Operating and dividing by Δt:

$$\frac{(1+\rho\Delta t)}{\Delta t}U$$
$$= \frac{(1+\rho\Delta t)}{\Delta t}b\Delta t + \frac{[\lambda_U\Delta t + \sigma(\Delta t)]}{\Delta t}\int \max\{U, W(w')\}\,dG(w')$$
$$+ \left(\frac{1}{\Delta t} - \frac{[\lambda_U\Delta t + \sigma(\Delta t)]}{\Delta t}\right)U$$

Note that:

$$\lim_{\Delta t \to 0} \frac{\sigma(\Delta t)}{\Delta t} = 0$$

Taking $\Delta t \to 0$ and rearranging:

$$\rho U = b + \lambda_U \int \max\{0, W(w' - U)\}\,dG(w')$$

Now using the decision rule:

$$\rho U = b + \lambda_U \left(\int_{-\infty}^{w^*} 0\,dG(w') + \int_{w^*}^{\infty} (W(w') - U)\,dG(w')\right)$$

Therefore:

$$\rho U = b + \int_{w^*}^{\infty} (W(w') - U)\,dG(w')$$

The value of employment, on the other hand, can be written as:

$$W(w) = w\Delta t + \frac{1}{1+\rho\Delta t}$$
$$\times \left\{ \begin{array}{c} [\eta(w)\Delta t + \sigma(\Delta t)]\,U + [\lambda_E\Delta t + \sigma(\Delta t)]\int \max\{W(w), W(w')\}\,dG(w') \\ + (1 - [\eta(w)\Delta t + \sigma(\Delta t)] - [\lambda_E\Delta t + \sigma(\Delta t)])\,W(w) \end{array} \right\}$$

Operating and dividing by Δt:

$$\frac{(1+\rho\Delta t)}{\Delta t}W(w) = \frac{(1+\rho\Delta t)\,w\Delta t}{\Delta t} + \frac{[\eta(w)\Delta t + \sigma(\Delta t)]}{\Delta t}U$$
$$+ \frac{[\lambda_E\Delta t + \sigma(\Delta t)]}{\Delta t}\int \max\{W(w), W(w')\}\,dG(w')$$
$$+ \left(\frac{1}{\Delta t} - \frac{[\eta(w)\Delta t + \sigma(\Delta t)]}{\Delta t} - \frac{[\lambda_E\Delta t + \sigma(\Delta t)]}{\Delta t}\right)W(w)$$

Taking one more time $\Delta t \to 0$ and rearranging:

$$\rho W(w) = w + \eta(w)(U - W(w)) + \lambda_E \int \max\{0, W(w') - W(w)\}\,dG(w')$$

Using the decision rule one more time:

$$\rho W(w) = w + \eta(w)(U - W(w))$$
$$+ \lambda_E \left(\int_{-\infty}^{w} 0\,dG(w') + \int_{w}^{\infty} (W(w') - W(w))\,dG(w')\right)$$

Therefore:

$$\rho W(w) = w + \eta(w)(U - W(w)) + \lambda_E \int_{w}^{\infty} (W(w') - W(w))\,dG(w')$$

It is known that $W(w^*) = U$ and $W(w) = W(w')$ hold for the reservation wages (in the unemployment state and in the on the job search case, respectively). Using the value of unemployment, it is possible to write:

$$U = \frac{b}{\left(\rho + \lambda_U\tilde{G}(w^*)\right)} + \frac{\lambda_U}{\left(\rho + \lambda_U\tilde{G}(w^*)\right)} \int_{w^*}^{\infty} W(w')\,dG(w')$$

Using the value of employment and evaluating in w^*:

$$w^* = \left(\rho + \eta(w) + \lambda_E\tilde{G}(w^*)\right)W(w^*) - \eta(w)U - \lambda_E \int_{w^*}^{\infty} W(w')\,dG(w')$$

Now given $W(w^*) = U$:

$$w^* = \left(\rho + \lambda_E\tilde{G}(w^*)\right)U - \lambda_E \int_{w^*}^{\infty} W(w')\,dG(w')$$

Replacing U in the last equation:

$$w^* = \frac{\rho + \lambda_E\tilde{G}(w^*)}{\rho + \lambda_U\tilde{G}(w^*)}\left[b + \lambda_U \int_{w^*}^{\infty} W(w')\,dG(w')\right] - \lambda_E \int_{w^*}^{\infty} W(w')\,dG(w')$$

Naming $\gamma(w^*) = \frac{\rho + \lambda_E\tilde{G}(w^*)}{\rho + \lambda_U\tilde{G}(w^*)}$ then:

$$w^* = \gamma(w^*)\left[b + \lambda_U \int_{w^*}^{\infty} W(w')\,dG(w')\right] - \lambda_E \int_{w^*}^{\infty} W(w')\,dG(w')$$

or alternatively:

$$w^* = \gamma(w^*)b + [\gamma(w^*)\lambda_U - \lambda_E]\int_{w^*}^{\infty} W(w')\,dG(w')$$

Now using the value of employment, the fact that $U = W(w^*)$ and calling $\theta(w) = \frac{1}{\rho + \eta(w) + \lambda_E\tilde{G}(w)}$:

$$W(w) = \theta(w)\left\{w + \eta(w)W(w^*) + \lambda_E \int_{w}^{\infty} W(w')\,dG(w')\right\}$$

The algorithm to solve the fixed point in the last two Bellman equations is the following:

1. Construct a grid in $w \in [0, \bar{w}]$. Guess $W_0(w)$ (for all values of w in the grid) and w_0^*.
2. Given $W_n(w)$ and w_n^* calculate $W_{n+1}(w)$ and w_{n+1}^* using:

$$w_{n+1}^* = \gamma(w_n^*)b + [\gamma(w_n^*)\lambda_U - \lambda_E] \int_{w_n^*}^{\infty} W_n(w')dG(w')$$

$$W_{n+1}(w) = \theta(w)\left\{ w + \eta(w)W_n(w_n^*) + \lambda_E \int_w^{\infty} W_n(w')dG(w') \right\}$$

3. If $|W_{n+1}(w) - W_n(w)| < \varepsilon$ and $|w_{n+1}^* - w_n^*| < \varepsilon$, then stop the iteration and the solution is $W_{n+1}(w)$ and w_{n+1}^*. Otherwise return to 2 with the following update (where λ is the step size):

$$W_{new}(w) = W_n(w) + \lambda\left(W_{n+1}(w) - W_n(w)\right)$$

$$w_{new}^* = w_n^* + \lambda\left(w_{n+1}^* - w_n^*\right)$$

Appendix B. Data manipulations

This appendix describes how the two main problems in the Social Protection Survey are handled, namely (1) appending the surveys conducted in different points in time and (2) dealing with the outliers in the labor income data.

The survey was conducted in 2002, 2004, 2006 and 2009 and in each survey, the interviewer explicitly asked about the events (dates of different states in the job market and average wages in each job) in the years after the last survey in which the individual participated. Only the surveys conducted in 2004 and 2006 are used for the estimations, and to avoid left and double censoring in the data, the data of the last spell in the 2002 survey is used to correct the first spells observed in the 2004 survey. The reasons for focusing only on these two surveys are twofold: (1) individuals were asked only about their labor histories but not about the wage in each event in the 2002 survey, and (2) the 2009 survey conveys information contaminated with the effects of the 2008 financial crises on the labor market. In any case, working only with these two surveys generates a time span from January 2002 to September 2007, which means that almost 6 years of labor market transitions are available for the estimation.

Two complications arose in the appending of the 2004 and 2006 surveys. First, there were overlapping events: events at the end of the 2004 survey overlapped with those at the beginning of the 2006 survey. Two overlapped events were merged if they belonged to the same state[30]. Second, there were contained events: events at the end of the 2004 survey were contained in those at the beginning of the 2006 survey. In this case, the events occurring in the 2004 survey were kept since it is assumed that the data on the events that occurred in the same year as the survey is more accurate. As mentioned previously, the last event of the 2002 survey was used only to correct for censoring and in this effort the criteria described above was also used when overlapping or contained events problems were found. The only difference is that information on wages was preserved for the employed spells observed at the beginning of the 2004 survey. Finally, individuals who presented inconsistencies in their

histories, and those who had incomplete histories or events with missing information on wages, hours worked or event dates were discarded[31].

The second problem is the existence of extremely high reported wages. Indeed, the average wage of the sample, without any adjustment, is US$208 and US$121 per hour for skilled and unskilled workers, respectively. These descriptive statistics contrast sharply with those obtained from another commonly used source of micro-data, the National Socio-economic Survey (CASEN). In 2006 the average wage was US$5.60 and US$1.80 per hour for skilled and unskilled workers, respectively. The source of the problem lies in the observations in the top 5% wages of the sample for both skill levels. In order to avoid the effect of these outlier observations the sample was trimmed. It is important to mention that in order to limit the discretions in the trimming process, percentiles were used and the trimming was done at both extremes of the sample. Table 6 shows descriptive statistics of the wages distribution and employment rates by skill level for different trimming levels (0.5, 1, 2 and 5 percentiles). Notice that eliminating the top and the bottom 5 percentiles generates average wages comparable with those observed in CASEN. The downside of choosing this trim level is of course the loss of information because 14 and 13% of the observation, for skilled and unskilled, respectively, are dropped. However, it is important to note that eliminating those observations barely affected the employment rate (see fourth column of Table 6) and, as expected, its effect is mostly noticeable in the right tail of the wages distribution (see Table 7). Additionally, due to the presence of measurement error in wages in the estimation procedure, the effect of trimming should be relatively limited on the value of estimated parameters of the wages distribution.

Table 6
Descriptive statistics on wages and employment rates under different trimming rates.

Trimming	Wages US$/hour	S.D. US$/hour	Emp. rate	No. of dropped individuals	%
Skilled workers					
0.5%	149.31	1105.91	90.1	20	1.8
1.0%	101.93	878.19	89.9	33	2.9
2.0%	12.50	211.77	89.9	70	6.2
5.0%	4.98	3.61	89.4	160	14.2
Unskilled workers					
0.5%	54.24	694.84	82.5	70	1.5
1.0%	11.65	260.15	82.4	137	3.0
2.0%	2.01	1.30	82.3	256	5.6
5.0%	1.89	0.91	81.8	602	13.2

Table 7
Wages distribution before and after the trimming procedure.

Percentile	Skilled		Unskilled	
	Raw sample US$/hour	Trimmed sample (5%) US$/hour	Raw sample US$/hour	Trimmed sample (5%) US$/hour
5%	1.14	1.39	0.79	0.94
25%	2.08	2.24	1.15	1.20
50%	3.63	3.75	1.61	1.65
75%	7.10	6.57	2.44	2.31
95%	19.88	12.28	5.29	3.75

---

[30] For the case of employed workers and to increase the likelihood of merging two events that belong to the same job, information about the type of contract (permanent, fixed term, per service, etc) was also used.

[31] This group of individuals with inconsistencies and missing data represented around 18% of the sample.

Appendix C. The likelihood function

The complete individual likelihood function of one cycle for individuals starting in an unemployment state is:

$$
L(\chi = 1) = \left\{ f_u(t_u, c_u = 1) \right\}^{c_u} \left\{ f_u(t_u) \int_{w^*} f_e(t_1, c_1 = 1 | w_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) dw_u \right\}^{(1-c_u)c_1}
$$

$$
\times \left\{ f_u(t_u) \int_{w^*} f_e(t_1, r_1 = 1 | w_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) dw_u \right\}^{(1-c_u)(1-c_1)r_1}
$$

$$
\times \left[\begin{matrix} f_u(t_u) \int_{w^*} f_e(t_1, r_1 = 0 | w_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) \times \\ \left(\int_{w_2} f_e(t_2, c_2^r = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2 | w_u) dw_2 \right) dw_u \end{matrix} \right]^{(1-c_u)(1-c_1)(1-r_1)c_2}
$$

$$
\times \left[\begin{matrix} f_u(t_u) \int_{w^*} f_e(t_1, r_1 = 0 | w_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) \times \\ \left(\int_{w_2} f_e(t_2, r_2 = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2 | w_u) dw_2 \right) dw_u \end{matrix} \right]^{(1-c_u)(1-c_1)(1-r_1)(1-c_2)r_2}
$$

$$
\times \left[\begin{matrix} f_u(t_u) \int_{w^*} f_e(t_1, r_1 = 0 | w_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) \times \\ \left(\int_{w_2} f_e(t_2, r_2 = 0 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2 | w_u) dw_2 \right) dw_1 \end{matrix} \right]^{(1-c_u)(1-c_1)(1-r_1)(1-c_2)(1-r_2)}
$$

The complete individual likelihood function of one cycle for individuals starting in an employment state is:

$$
L(\chi = 0) = \left\{ \int_{w^*} f_e(t_1, c_1 = 1 | w_1) \frac{1}{w_1} q\left(\frac{w_1^o}{w_1}\right) f_w(w_1) dw_1 \right\}^{c_1}
$$

$$
\times \left\{ \int_{w^*} f_e(t_1, r_1 = 1 | w_1) \frac{1}{w_1} q\left(\frac{w_1^o}{w_1}\right) f_w(w_1) dw_1 \right\}^{(1-c_1)r_1}
$$

$$
\times \left[\begin{matrix} \int_{w^*} f_e(t_1, r_1 = 0 | w_1) \frac{1}{w_1} q\left(\frac{w_1^o}{w_1}\right) f_w(w_1) \times \\ \left(\int_{w_2} f_e(t_2, c_2^r = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2 | w_1) dw_2 \right) dw_1 \end{matrix} \right]^{(1-c_1)(1-r_1)c_2}
$$

$$
\times \left[\begin{matrix} \int_{w^*} f_e(t_1, r_1 = 0 | w_1) \frac{1}{w_1} q\left(\frac{w_1^o}{w_1}\right) f_w(w_1) \times \\ \left(\int_{w_2} f_e(t_2, r_2 = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2 | w_1) dw_2 \right) dw_1 \end{matrix} \right]^{(1-c_1)(1-r_1)(1-c_2)r_2}
$$

$$
\times \left[\begin{matrix} \int_{w^*} f_e(t_1, r_1 = 0 | w_1) \frac{1}{w_1} q\left(\frac{w_1^o}{w_1}\right) f_w(w_1) \times \\ \left(\int_{w_2} f_e(t_2, r_2 = 0 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2 | w_1) dw_2 \right) dw_1 \end{matrix} \right]^{(1-c_1)(1-r_1)(1-c_2)(1-r_2)}
$$

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