Households' Financial Vulnerability *

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Abstract

Households financial vulnerability determines households' default risk. Financial stability could be affected by households behaviour under stressing macroeconomic conditions. Households financial vulnerability depends on their indebtedness levels and on the fragility of their income sources to be able to fulfill their obligations. The main source of households uncertainty comes from labour income generation, which is critically determined by unemployment. Heterogeneity of indebtedness levels and of income uncertainty calls for microeconomic analysis. This paper uses panel data survival analysis to estimate the probability of job loss at the individual level. Using semiparametric methods, a significant heterogeneity is found for the impact of aggregate unemployment among individuals. Monte Carlo simulations are run to assess households financial stress and then to estimate aggregate *debt at risk* under high unemployment rates scenarios. Since the majority of debt is held by those with lower levels of income vulnerability, it is found that financial stability is not significantly affected by high unemployment levels.

Keywords: Financial vulnerability, household finances, household indebtedness.

JEL Classification: I31, J01.

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1 Introduction

Households financial vulnerability determines households' default risk. Financial stability could be affected by households behaviour under stressing macroeconomic conditions. Households financial vulnerability depends on their indebtedness levels and on the fragility of their income sources to be able to fulfill their obligations. The main source of households uncertainty comes from labour income generation, which is critically determined by unemployment. Heterogeneity of indebtedness levels and of income uncertainty calls for microeconomic analysis. This paper uses panel data survival analysis to estimate the probability of job loss at the individual level. Monte Carlo simulations are run to assess households financial stress and then to estimate aggregate *debt at risk* under high unemployment rates scenarios.

Microdata allows to capture heterogeneity among households beyond aggregate data. The impact of macroeconomic shocks to financial stability will be defined by the heterogeneity of indebted households. Household financial data is scarce and this is one of the reasons why there is no abundance of household level studies to assess household financial indebtedness. The recent Chilean Survey of Household Finances (Encuesta Financiera de Hogares - EFH) run by the Banco Central de Chile contributes with novel information for this type of analysis.

The main objective of this paper is to carry out a household stress test at the micro level that allows to quantify the household *debt at risk* when facing aggregate shocks. Evidence from debt issuers indicate that the main reason for household to default is unemployment. Accordingly, this paper will focus in labour income risk associated to the probability of job losing when aggregate unemployment rate shifts.

Nordic countries have been leading this sort of analysis. In fact, the Sweedish Central Bank, (Riskbank) has published a series of simulations based on micro data (Riksbank, 2006, 2007). They found that Sweedish households are not particularly vulnerable to shifts in interest rates and/or unemployment rates. They find that 6.3% of households have what they call negative margin, concentrating 5.6% of total household debt (debt at risk). Unemployment rates increases of 1-3 percentage points imply that households without margin increase to 6.7% and debt at risk increases to 6.3%. Norwegian Central Bank (2006) also carries out a similar exercise, finding that 19% of households have negative margin, and that 16% of total debt is held by those households. They conclude that low and median income groups hold the majority of the exposed debt and have increased they participation.

However, the Nordics do not take into account that aggregate unemployment affects very differently agents across households. In fact, they consider that the probability of falling into unemployment is uniform for all workers. This is a very strong assumption and bias the results depending on the distribution of debt among individuals. In Chile, there is evidence that unemployment is less frequent among those with high education groups and of middle age (Neilson and Ruiz-Tagle, 2007).

Section 2 analyses the distribution of household indebtedness in Chile and discusses *debt at risk* using the EFH 2007 data. Section 3 estimates job loss probabilities using the Social Protection Survey Panel (Encuesta de Proteccin Social - EPS) data waves 2002 and 2004, covering a 10-year period 1995-2004. Non parametric and Semiparametric methods are used to estimate the impact of aggregate unemployment rates on individual job loss probabilities. Section 4 carries out simulations of *debt at risk* under different scenarios. For this purpose, job loss probabilities are imputed into the EFH data, and then Monte Carlo simulations are run to assess the distribution of the stress test. Finally, section 5 concludes.

2 Household indebtedness and *debt at risk*

Household indebtedness in Chile has received considerable attention in recent years because of the financial deepness process that has been experimented in the economy. Debt's growth rate has constantly surpassed that of real GDP during the last decades. The ability to pay back debts by households and the amount of debt they hold determine how much of this debt could be considered *at risk* of not being recovered by credit issuers.

Households' real banking debt represents more than 70% of total household debt (see Figure 1) and has grown more than 15% in average in real terms between 2003 and 2008. Therefore, real banking debt has almost doubled during this period while real GDP increased almost 30% during the same time.

Total debt growth has also surpassed households' disposable income growth; hence debt to disposable income ratio has grown significantly over the last years. In the second quarter of 2008, this aggregate indicator has reached 68% from 42% in the second quarter of 2003. Furthermore, the financial service burden to disposable income ratio has also expanded from 14% to 22% over the same period (see Figure 1).

Since banking debt is by far the most important household debt, exposure of the banking system to household sector is a matter of concern from a financial stability perspective. Banking exposure, measured as the sum of total mortgage and consumer loans as a percentage of total banking loans, has increased to more than 33% in 2008 from 15% at the beginning of the 1990s.

Even though Chilean households are increasing their debts, there are no clear signs that Chile is following a trend significantly different from other countries. In fact, the relationship between households debt to GDP and per capita GDP suggests that household debt is not a significant share of GDP. Nevertheless, the financial service burden to disposable income ratio is not particularly low compared to its economic development -measured as the per capita GDP (see Figure 2). This last observation is related to the length of the loans and the high interest rates, when compared to developed economies.

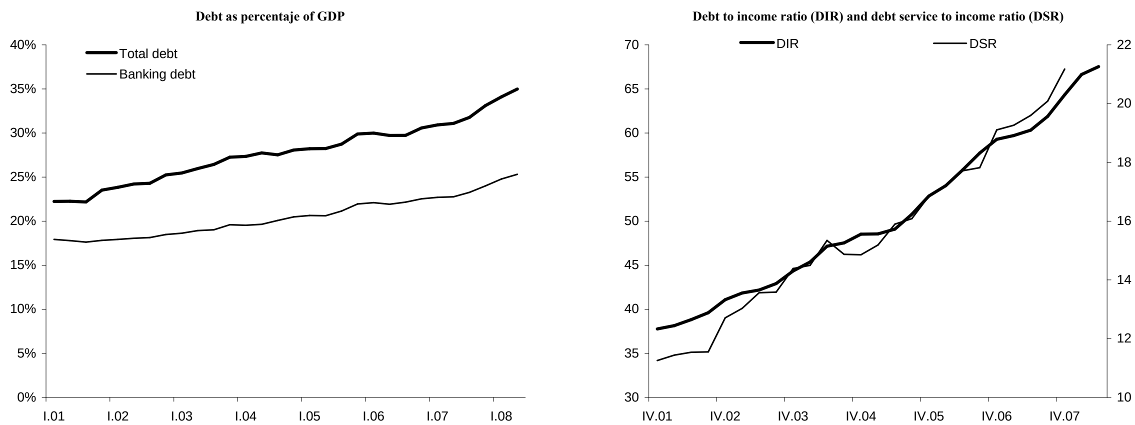
Figure 1: Chilean Households indebtedness at the macro level

(a) Households debt as percentage of GDP

(percentage)

(b) DIR and DSR

(percentage)



Source: Central Bank of Chile.

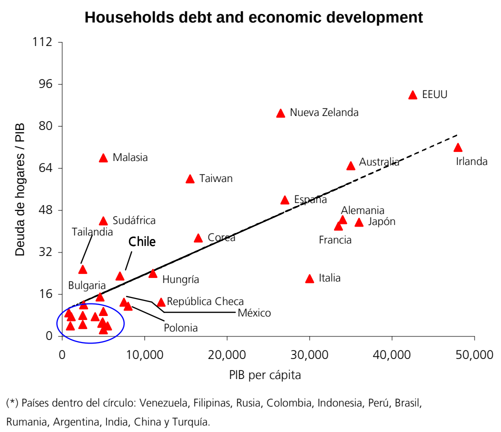
In parallel, analysis at a microeconomic level shows an important heterogeneity among Chilean households. The most noticeable fact is that the vast majority of debt is held by high income groups. This is particularly important in Chile because of the high levels of income inequality. In fact, debt distribution maps rather well income distribution.

Different microeconomic surveys show this similar pattern, though it may be slightly changing over time, suggesting a financial deepening process (see Figure 3 and 9). Moreover, households behavior in terms of their ability to pay back debts may vary considerably depending on their debt levels and on their income levels. This is an important reason to consider households heterogeneity when analyzing households

Figure 2: Household debt: International comparison

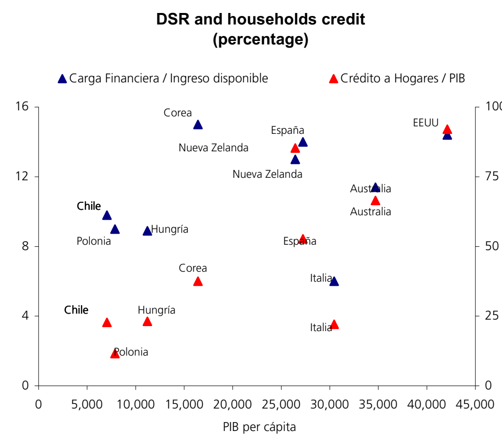
(a) Households debt and economic development

(percentage, US dollars)



(b) DSR and household debt

(percentage)



Source: IMF, Global Financial Stability Report 2006.

financial vulnerability.

In what follows of this section datasets are described and a discussion of the *debt at risk* methodology is presented.

2.1 The Chilean Survey of Households Finances

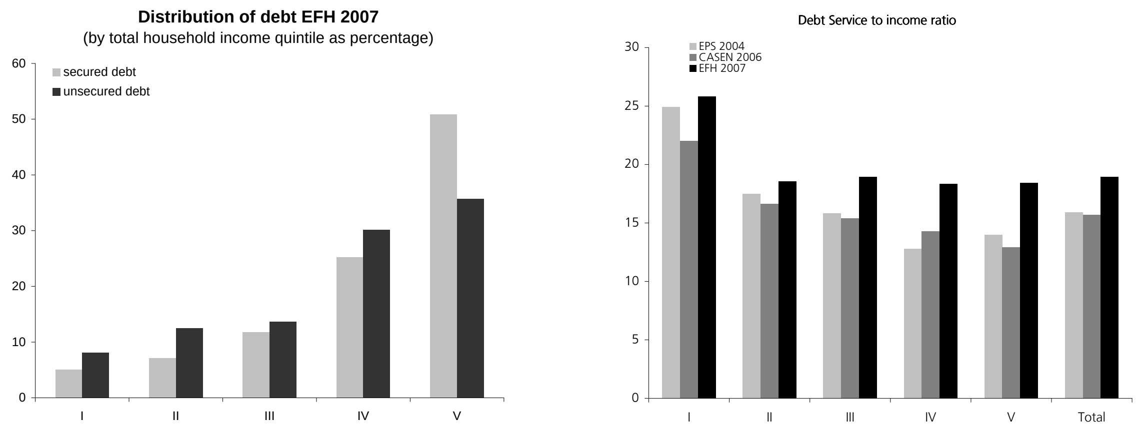
The Chilean Survey of Household Finances (Encuesta Financiera de Hogares -EFH) has been conducted by the Central Bank of Chile for the first time during 2007. This initiative, pioneer in the region, asks detailed questions about labour status, real estates ownerwship, financial assets, debts, perceptions about debt service, access to credit, pensions, insurances and savings.

The EFH 2007 included 4,021 households, being representative at a national urban level. Furthermore, since there are many assets held by only a small fraction of the population, this survey also has an oversample of the wealthier households. Thanks

Figure 3: Chilean Households indebtedness at the micro level

(a) Distribution of debt by income quintiles (percentage, US dollars)

(b) DSR by income quintiles (percentage)



Source: Authors' own calculations based on EFH2007.

to the collaboration of the Tax Office (Servicio de Impuestos Internos) it was possible to obtain a sample with a significant oversampling of the high wealth households. Therefore, the EFH 2007 constitutes the only statistical source in Chile that provides complete information about the balance sheets of the households as well as their ability to service financial commitments.

2.2 Debt distribution and *debt at risk*

There is no such a common knowledge definition of *debt at risk*. So far, the Chilean Central Bank[1] has used a definition of *debt at risk* based on high levels of "Debt Service Ratio" (debt service over income ratio). On the other hands, Nordic countries have considered "negative margins" (total spendings > total income). Also, they included liquid and illiquid assets as debt backup. For household h, the "margin" is computed as:

$$M_h = Y_h - DS_h - E_h, \tag{1}$$

[1] See Cox, Parrado and Ruiz-Tagle (2007).

where Y is household total income, DS is debt service, and E is household total expenditures.

The base scenario of *debt at risk* is built considering two dimensions: Negative financial margin and high DSR. Data collection posses two problems for interpretation: First, there is a risk of double counting, e.g., clothes expenditure could also appear as debt if payed in statements; second, if a significant part of total expenditure is made through credit in statements (including supermarket expenditure for example) the DSR indicator could actually overestimate the financial stress of the households.

Taking into account these caveats, a base scenario for *debt at risk* is built considering both negative financial margin and high DSR. Negative financial margin is set at 20% excess expenditure over income. DSR is considered at above 50 and above 75. Table 7 presents results for the base scenario of *debt at risk* based on the debt service ratio (DSR) and the financial margin. It can be observed that 13.6% of households exhibit negative margin and DSR larger than 50 percent, holding 20% of total debt. A more refined assessment of *debt at risk* considers DSR above 75 percent, indicating that 9.5% of households are higly financial stressed and total debt at risk reaches 16% (15% of secure debt and 19% of unsecure debt).

3 Assessing financial vulnerability

Households financial vulnerability is mainly due to the income sources. The principal households income source is labour income of their members. Labour income can be lost if the job ends due to any reason, either voluntary or involuntary. At any time, workers face a certain probability of losing their jobs. Estimating this job loss probabilities allows to impute those probabilities to those working individuals to assess their financial vulnerability when financial information is available.

There are no available estimations of job loss probabilities in Chile .[2] This section provides estimations of job loss probabilities using survival analysis with non-parametric and semiparamteric methods. In particular, the interest is focused on the effect of aggregate unemployment rate on job loss probabilities.

Both in a static and in a dynamic framework, the effects of aggregate unemployment are heterogeneous. Given that the distribution of households debt is diverse, the impact of higher unemployment levels generates non homogeneous effects on *debt at risk*. The Nordics proposed a simplified analysis assuming that unemployment shocks affects all individuals in the same manner. Although limited, that methodology makes sense for them because the distribution of debt in those countries is much flatter than in Chile (particularly in Norway), and also because they have large unemployment benefits. In contrast, for Chile it looks more adequate to estimate disaggregate job loss probabilities to assess heterogeneous impacts.

3.1 Job loss probabilities

Estimating job loss probabilities requires survival analysis. In this case, job loss probability mirrors the probability of staying employed. What is estimated then is the probability of surviving employed at a given moment of time t.

Let T be a non-negative random variable denoting the time to failure event (in this case failure is job loss). The survival function is the reverse of the cumulative distribution function of T ($F(t)$):

$$S(t) = 1 - F(t) = \Pr(T > t), \tag{2}$$

and it reports the probability of surviving beyond time t, where the density function is simply $f(t) = -S'(t)$.

[2]There are only estimations for unemployment duration.

The cumulative hazard function is defined as:

$$H(t) = -\ln\{S(t)\}, \tag{3}$$

so that,

$$f(t) = h(t)\exp\{-H(t)\}. \tag{4}$$

For the purpose of this paper, what is interesting is the how some covariates affect the hazard function, which requires multivariate analysis. Nevertheless, simpler non-parametric analysis can be used to compare different group's hazard functions. This is done by estimating the survival function through the Kaplan-Meier (1958) estimator given by:

$$\hat{S}(t) = \prod_{j|t_j \leq t} \left(\frac{n_j - d_j}{n_j} \right), \tag{5}$$

where n_j is the number of individuals at risk at time t_j and d_j is the number of failures at time t_j.

On the other hand, the Cox (1972) semi-parametric model requires no parametric form of the survival function and assumes that covariates shifts multiplicatively the baseline hazard function. For the jth subject, the hazard function is:

$$h(t|X_{j,t}) = h_0(t)\exp(X_{j,t}\beta_x), \tag{6}$$

where the β_x are to be estimated from the data.

The baseline function $h_0(t)$ is not parametrised (actually it is not estimated), because the model is proposed in terms of ratios (individual j compared to individual m):

$$\frac{h(t|X_{j,t})}{h(t|X_{m,t})} = \frac{\exp(X_{j,t}\beta_x)}{\exp(X_{m,t}\beta_x)}. \tag{7}$$

The Cox model is rather convenient for the purpose of this paper because it is easy to compute and can provide predicted probabilities given the covariates.

Parametric methods require imposing a functional form to the baseline hazard function. The most common are Weibull, Exponential, Lognormal, Gamma, Loglogistic.

These models are computationally costly, and have also the disadvantage of bias in case of an inappropriate distributional assumption.

This papers combines different non-parametric, semi-parametric, and parametric methods in order to be able to predict accurately job loss probabilities.

3.2 The data

Since 2002 a novel panel survey called Social Protection Survey (Encuesta de Proteccin Social, EPS) has been carried out in Chile every two years. The survey was designed to assess the well being of workers and nonworkers and their households.[3] The EPS accounts for 16,727 observations that represents the population of Chile aged 18 and more in 2004.

In the 2002 wave, the individuals were asked to remember every single labor story since 1980 up to date in a chronological way. Each story had an beginning date and an ending date. For each story the individual was asked about his employment status, characteristics of the job and some qualitative questions. In the 2004 wave, individuals were asked to remember the missing history, i.e., the stories that occurred since 2002 the interview in 2004.

The data is then set up so that we have a monthly panel of individuals with the corresponding employment information in each period of time. Then, for each month we know the employment status of a sample that is representative of the Chilean population aged 18 and more in 2004. Representativeness in past years is narrowed to a varying age group. For instance, in 2004 the data is representative of the people between 18 and 65 years old, in 2003 the data is representative of the people between 18 and 64 years old, and so on.

[3]The EPS was designed jointly by Ministry of Labor and the Center for Microdata of the University of Chile, with the close collaboration of the University of Pennsylvania.

In this paper, a ten year period, from 1995 until 2004, has been chosen. This is because in this period Chile experienced the effects of the Asian crisis with a relatively short mild recession in 1999 and 2000. Unemployment rate rose significantly and remained higher for a long period afterward. This implies that the sample is compound by 16,727 individuals observed around 120 times, which implies that the dataset has around 2 million records.

3.3 Estimation results

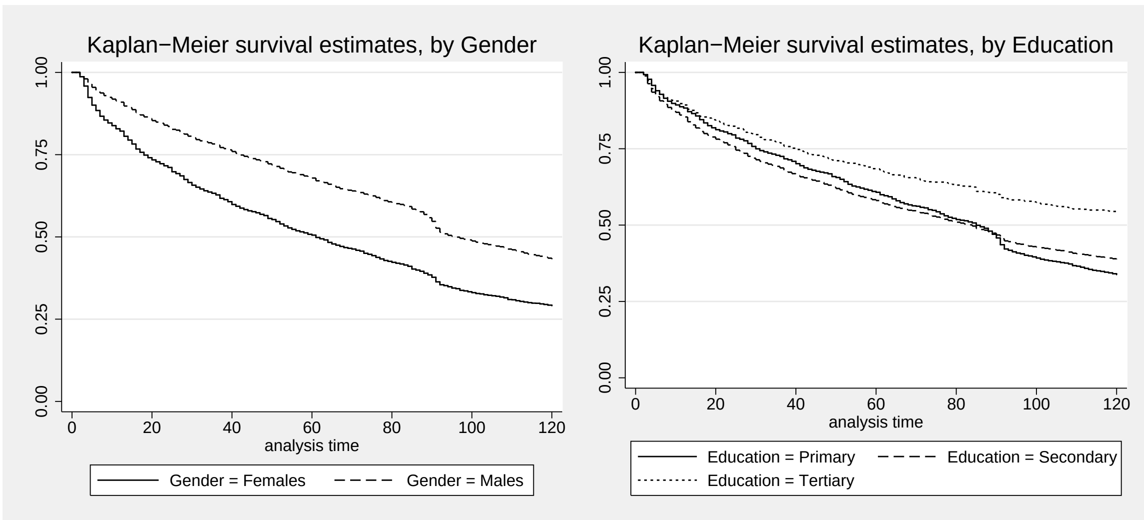
Using the labour stories from the EPS 2002 and 2004, job loss probabilities are estimated. Those probabilities are estimated using a set of individual characteristics $X_{j,t}$ and a set of time variant aggregate variables $Z_{j,t}$. The $X_{j,t}$ vector of variables includes gender, age, education, job contract, marital status, economic sector of the job, size of the firm, among others. The $Z_{j,t}$ vector of variables considers unemployment rate and monthly activity indexes.

It is important to mention that job loss is defined as any exit from job, both to unemployment and to inactivity. This is because the objective of this exercise is to assess the ability of households to cope with their financial obligations, so that any decay in income will affect household financial stress.

It is useful first to look at the Kaplan-Meier non-parametric estimates of the survival functions. Figure 4 presents estimations of the survival function by gender and educational level. What is interesting to note is that males are less likely to lose employment at any time. In fact, the mean estimator indicates that males remain employed 50% longer times than females, and the probability of losing employment reaches 50% only after 80 months for both genders.

On the other hand, those with tertiary education have a much lower probability of losing employment than those with primary and secondary education. In parallel, workers with secondary education compared to those with primary education have a larger probability at shorter employment duration and a lower probability after ninety months.

Figure 4: Job loss probabilities



Source: Authors' own calculations using EPS 2002 and 2004.

Multivariate analysis using the Cox's semi-parametric estimations of the proportional hazard model was carried out for multiple specifications. Table 1 presents our preferred model. A series of interesting results emerge clearly from the data. First, males have around 30% lower probability than females to lose employment and the unemployment rate shifts that probability in 17%. However, unemployment seems to have a much larger effect on males than females (around 8% per unemployment percentage points).

Second, age has a negative decreasing effect on job losing probabilities. This indicates that younger workers are much more likely to lose employment at any given moment of time. However, that effect fades as age increases.

Third, workers with higher levels of education face a significantly lower probability of employment loss. Those with tertiary education have about 30% lower probablity than those primary education only. Also, those with tertiary education have about 60% less probability of employment loss.

The effect of the unemployment rate is also heterogeneous among different education groups. In fact, workers with tertiary education have a 5% lower probability per unemployment percentage point (implying about 45% lower probability on average) than those with primary education only. Workers with secondary education face a 3% lower probability per unemployment percentage point (implying about 27% lower probability on average) than those with primary education only.

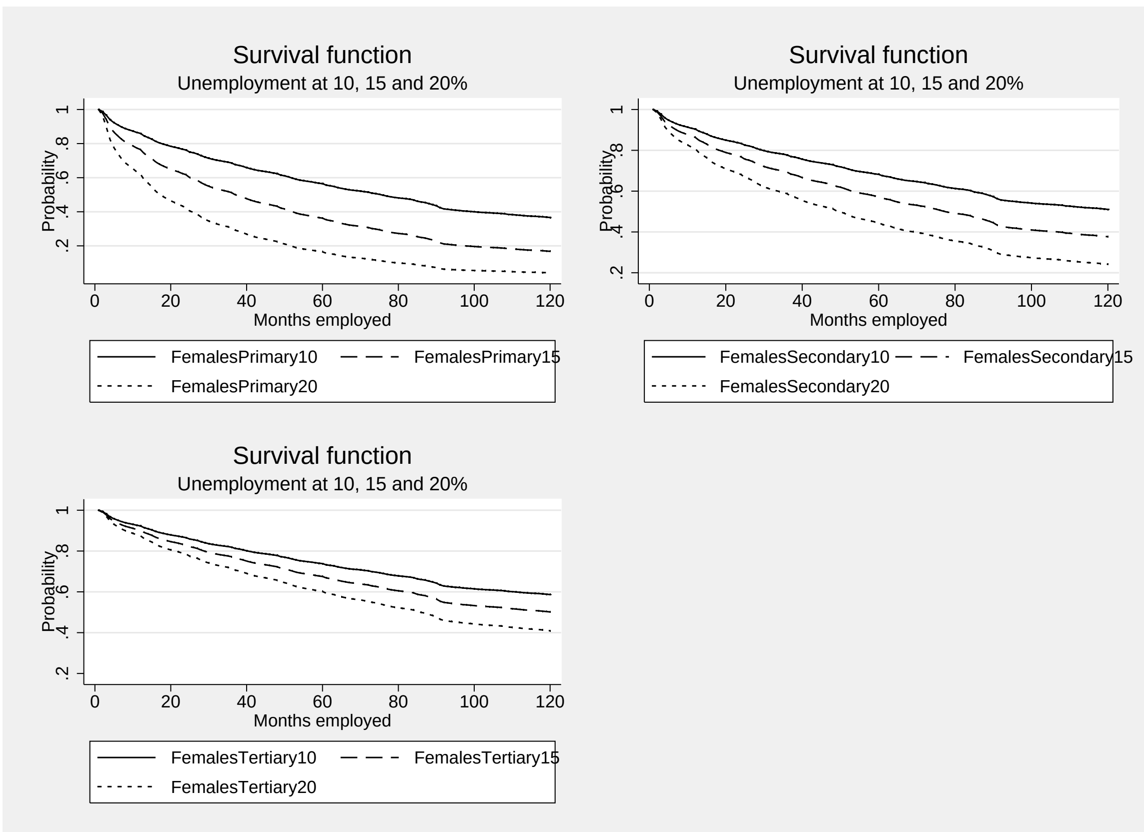
Table 1: Cox Estimations of Job Loss Probabilities

(coefficients in $\exp(\beta)$ form)

Variable	Haz. Ratio	Std. Err.	z	P> $\|z\|$	[95% Conf.	Interval]
Males=1	.3326779	.0236855	-15.46	0.000	.2893485	.3824957
Age	.8659158	.0045911	-27.15	0.000	.8569641	.874961
Age^2	1.001452	.0000652	22.28	0.000	1.001325	1.00158
Unemp.Rate	1.121433	.0058121	22.11	0.000	1.110099	1.132882
Unemp.R.*(Males=1)	1.064744	.0065273	10.23	0.000	1.052027	1.077614
Unemp.R.*(EducS=1)	.960692	.0017416	-22.12	0.000	.9572847	.9641115
Unemp.R.*(EducT=1)	.9768453	.0044419	-5.15	0.000	.9681781	.9855902
No. Subjects	12906					
No. failures	10907					
No. Observations	1295487					
Time at risk	1301439					
Log likelihood	-99708.428					
LR chi2(7)	3661.31					

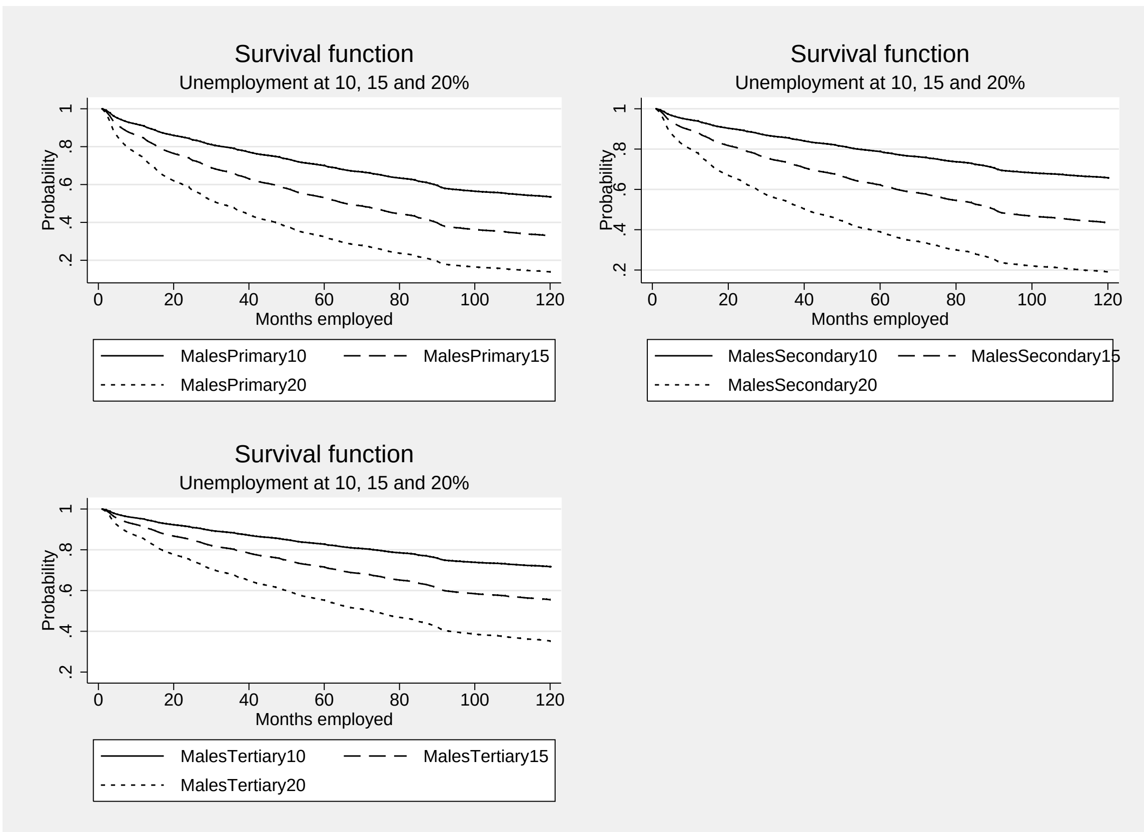
From the Cox's estimations we can predict job loss probabilities through the survival functions. Figures 5 and 6 shows the survival functions estimations for females and males respectively. Age was set at mean values (around 41 years old), and unemployment shifts were set at 10%, 15%, and 20%. Its is clear from the graphs that higher educationl attainment diminishes job loss probabilities and also diminishes the impact of a an aggregate unemployment shift. It can also be observed that females exhibit higher probabilities of job loss (the survival functions are lower), but that aggregate unemployment shifts affects considerably more males than females.

Figure 5: Job loss probabilities



Source: Authors' own calculations using EPS 2002 and 2004.

Figure 6: Job loss probabilities



Source: Authors' own calculations using EPS 2002 and 2004.

4 Financial stress simulations

This section is devoted to the analysis of higher unemployment rates simulations and their effects on *debt at risk*. Monte Carlo simulations are run on the probability of losing employment for each of the worker individuals in each household. Employment loss probabilities are taken from section 3 and then imputed to the EFH dataset.

The first problem faced for this exercise is that the EFH does not contain information about employment duration. Employment loss probabilities depend critically on the duration of the job, hence employment duration has to be imputed. In order to do so, workers are separated into cells by age group and education attainment. For each cell, the whole distribution of employment duration is computed as $\hat{d}_c$. Then, every worker j in cell c will be assigned a random employment duration following the actual distribution $\tilde{d}_c \sim \hat{d}_c$. Hence, this is the first source of randomization.[4]

Then, the simulations are ran as follows. First, a uniform random number $u_{j,h}$ is assigned to each worker in the EFH. For each worker in the EFH with an assigned employment duration $\tilde{d}_c$ with characteristics $X_{j,h}$ and under the scenario given by Z^t, a probability of job loss from the estimated hazard function is computed. If that probability falls below the threshold given by the random number, the worker will be considered as employed. If not, the worker will be considered as if he had lost his employment, so that his labour income will become equal to zero.

$$\hat{Y}^t_{j,h} = Y^t_{j,h} \times \mathbf{1}\left(\hat{\Pr}^t_{j,h}\left(X^t_{j,h}, Z^t\right) > u\right). \tag{8}$$

The second source of randomization comes the fact that the simulated employment loss probability contains the uncertainty respect to the survival model estimation through the probability of loosing the job.

After the employment condition of the worker is redefined and his corresponding

[4]The actual cumulative density function, $\Phi\hat{d}_c$, was approximated by a 9-degree polynomial in order to be used for simulations. Figures 10 and 11 shows those estimations.

labour income recomputed, overall household income is computed again. The, DSR must be refreshed to reflect the simulated total household income. Finally, aggregate indicators of *debt at risk* are computed again for the whole sample.

In the base scenario, 61% of total households hold any sort of formal debt. In fact, 16% of households hold secure debt and 57% hold unsecure debt. Secure debt is 60% of total debt (unsecure debt is 40%). On the other hand, 45% of total debt is held by upper richest quintile (51% of secure debt and 36% of unsecure debt). Besides, median DSR is 19.5% for all indebted households.

Table 2 presents the results of the simulations.[5] In the base scenario, considering DSR above 75% and negative margin above 20%, 9.5% of households are under considered with debt at risk, which accounts for 16.1% of total households debt.

Then, underlying job loss probabilities are included in order to add to the current debt at risk, the households that could have members losing their jobs and then fall into higher financial stress. This makes shifts household under financial stress to between 13% and 16%, and total debt at risk to between 20% and 25% in a 95% confidence interval.[6]

Next, unemployment rate is increased by 5%, which is more than the shift during the Asin crisis. Under this scenario, the number of households under high financial stress increases from to between 16% and 19%, and debt at risk increases to between 22% and 28%. A more stressing scenario with an increase of unemployment in 15% increases the number of highly stressed households to between 25% and 28%, and *debt at risk* to between 31% and 38%. These results indicate that significant increases in aggregate unemployment rate do not imply necessarily a significant increase in *debt*

[5] 500 Monte Carlo simulations were used. Exercises with 1,000 and 5,000 simulations made no significant changes.

[6] 95% confidence intervals were build non parametrically using simulation percentiles.

at risk compared to the actual situation.

The implications of these results are that higher levels of unemployment similar what was observed during the Asian crisis do not necessarily imply that the financial system will suffer a significant default shock by households. In fact, this would increase debt at risk only in around 4 percentage points (comparing to the base scenario including underlying job loss probabilities). Nevertheless, this does not mean that the financial system can overlook households debt.

Table 2: Households with negative margin

(Intervals for simulations are p(2.5) to p(97.5))

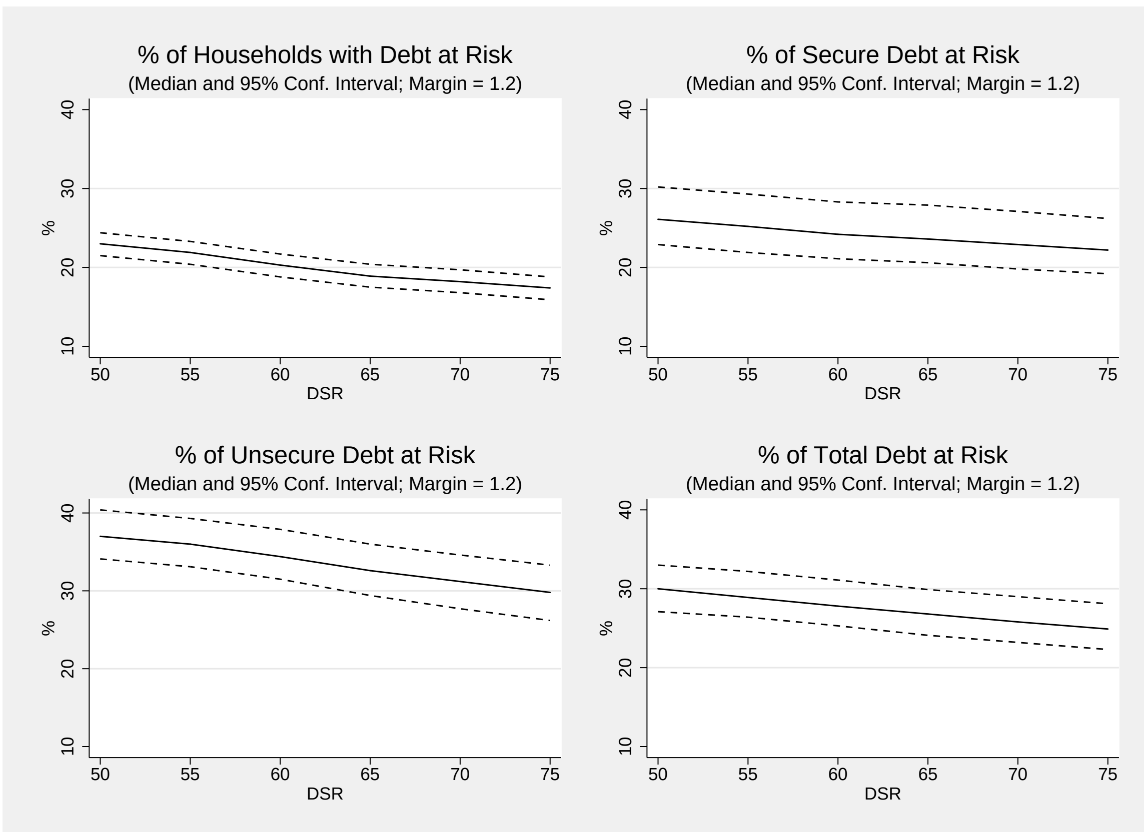
	% Households	% Secured Debt	% Unsecured Debt	% Total Debt
Base scenario				
DSR>50	13.6	17.1	26.1	20.2
DSR>75	9.5	14.5	18.8	16.1
Base scenario + underlying job loss probability				
DSR>50	18.2 - 20.8	20.3 - 26.3	30.8 - 36.5	24.3 - 29.4
DSR>75	13.2 - 15.6	17.1 - 22.6	23.1 - 29.0	19.7 - 24.6
Δ^+ 5% Unemployment				
DSR>50	21.5 - 24.4	22.9 - 30.2	34.1 - 40.4	27.1 - 33.0
DSR>75	15.9 - 18.8	19.2 - 26.2	26.2 - 33.3	22.3 - 28.1
Δ^+ 10% Unemployment				
DSR>50	26.1 - 29.5	26.7 - 35.3	38.7 - 45.6	31.2 - 38.3
DSR>75	20.1 - 23.3	22.8 - 30.2	30.9 - 38.8	25.9 - 32.6
Δ^+ 15% Unemployment				
DSR>50	31.0 - 34.6	31.9 - 40.9	44.3 - 51.4	36.6 - 44.3
DSR>75	24.5 - 28.0	27.0 - 35.3	36.4 - 44.3	31.0 - 37.9

Source: Authors' own calculations using EPS 2002 and 2004 and EFH 2007.

The DSR cut level of 75% can be considered as a not so demanding condition for considering a household under high financial stress. Although Table 2 also includes the cut level at 50%, Figure 7 complement the anlysis by presenting a variety of DSR cut levels under an unemployment shift of 5% and with negative margin at 1.2. The conclusion of the inspectio of those graphs is that results are failry stable, without presnting extreme shifts in debt at risk.[7]

Figure 7: Debt at Risk Simulations at different DSR cut-levels

(Unemployment shift of 5%)

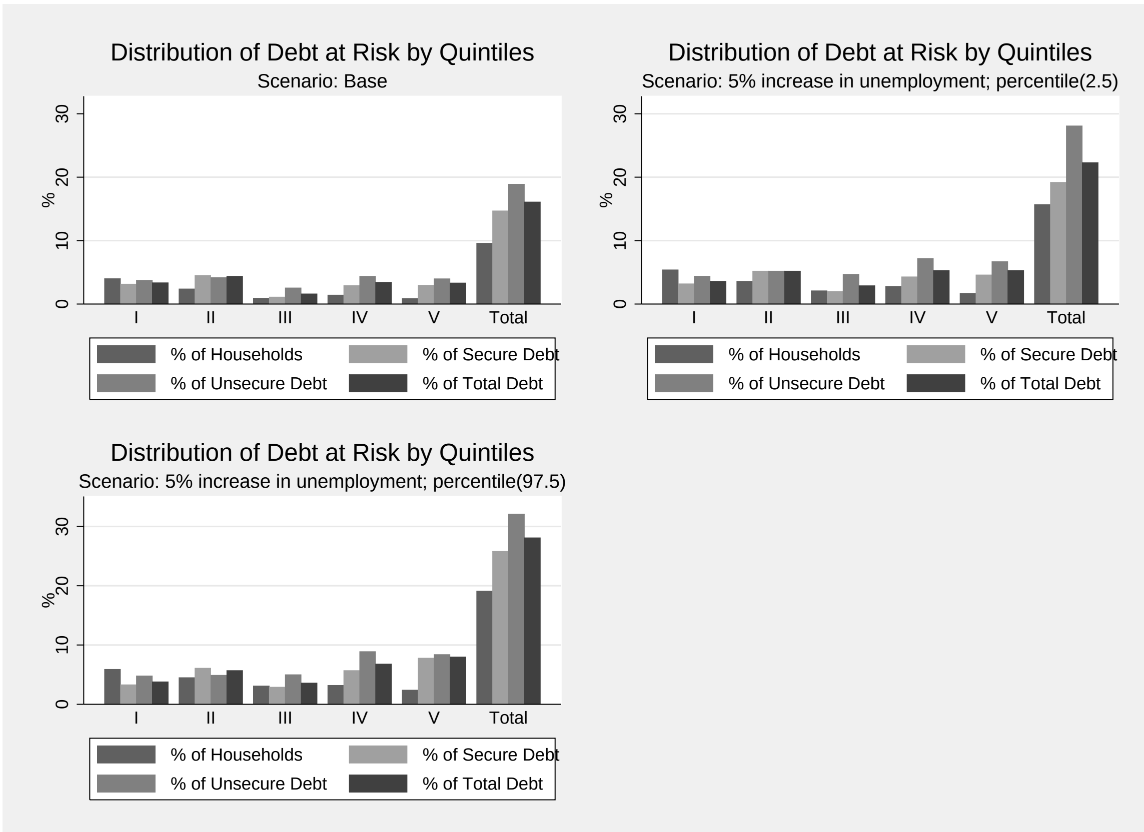


An additional interesting analysis is to look at the distribution of the effects by income quintiles. Figure 8 presents the base scenario plus the extreme scenarios (percentiles 2.5 and 97.5) under a 5% increase in aggregate unemployment rate. It can be observed that when unemployment increases, for the debt at risk to increase significantly, it has to occur that the households in high income quintiles suffer from unemployment. From the estimations of the job loss probabilities we know that this is less likely to

[7]Figure 12 also presents the exercise with negative margin at 1.1.

occur under all circumstances, implying monitoring should be placed on high-income high-debt households.

Figure 8: Debt at Risk Simulations by Quintiles



Finally, some caveats should be considered. There is a number of issues that are not considered in this simulation exercise. First, as workers face non-negative unemployment probabilities, unemployed (and inactive) workers face a non-negative probability of becoming employed and then to be able to contribute with labour income to household financial resources, making financial situation less stressing. Second, workers that become unemployed may have unemployment insurance, although in Chile this does imply a significant source of income.[8] Third, workers who retire to inactivity may have pension income. Fourth, households that suffer from unemployment may

[8]Unemployment insurance covers 30% of earnings for 3 months for a worker whos was employed at least 12 consecutive months.

use other sources of income to face their financial obligations, making default less likely to occur. Fifth, households who suffer from unemployment may liquify assets in order not default. Neverthless, all these caveats go in the same direction, which is to make this simulation exercise less stressing for households' financial situation. Consequently, this exercise should be considered as un upper bound situation which not quite likely to occur.

5 Conclusions

Indebtedness of the household sector has increased significantly in the previous years in Chile. However, no analysis had been carried out so far to assess how vulnerable could households be to unemployment shifts in terms of their financial stress. This paper contributes with a novel analysis to attempt to quantify the risks associated for financial stability.

Fragility of households' main income source, labour income, shows significant heterogeneity, implying that micro level studies must be used to assess aggregate impacts of unemployment on financial stress. It has been found that gender, age, and education determine the impact of unemployment shocks on the probability of losing a job.

The concentration of household debt in high income households recalls that heterogeneous responses to unemployment may have important implications for financial stability. In fact, the simulations carried out on the different shocks scenarios show that *debt at risk* is rather bounded.

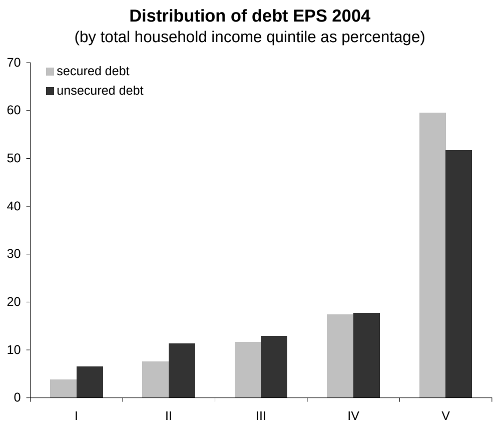
The implications of these results are that higher levels of unemployment do not necessarily imply that the financial system will suffer a significant default shock by households. Nevertheless, the this does not mean that the financial system can overlook households debt.

Appendix

Figure 9: Chilean Households indebtedness

(a) Distribution of debt by income quintiles

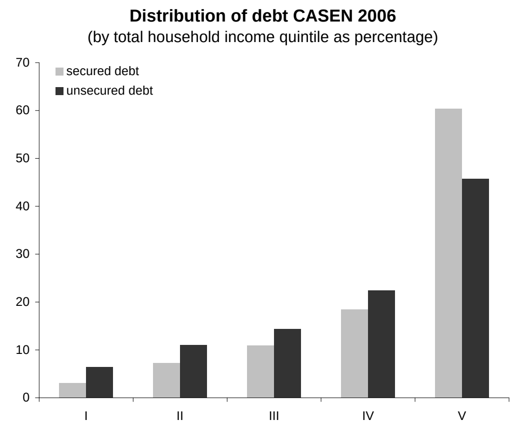
(percentage, US dollars)



Source: Authors' own calculations based on EPS2004.

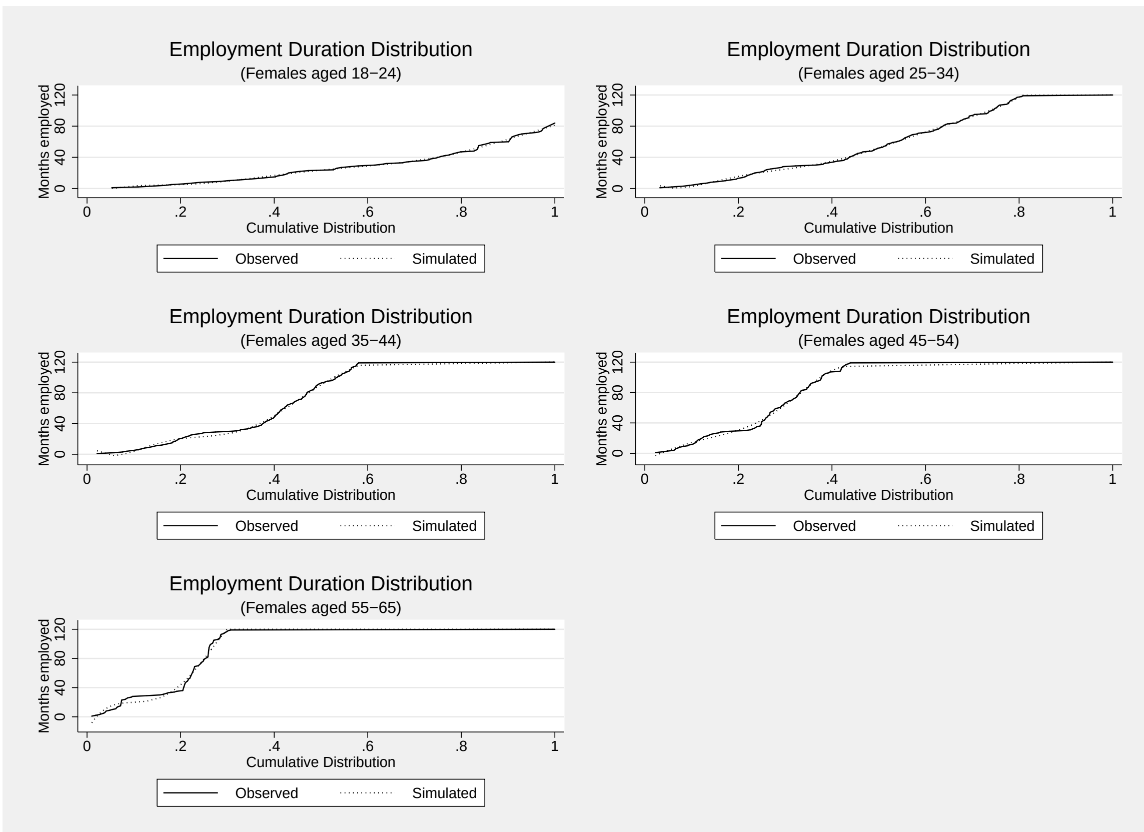
(b) DSR by income quintiles

(percentage)



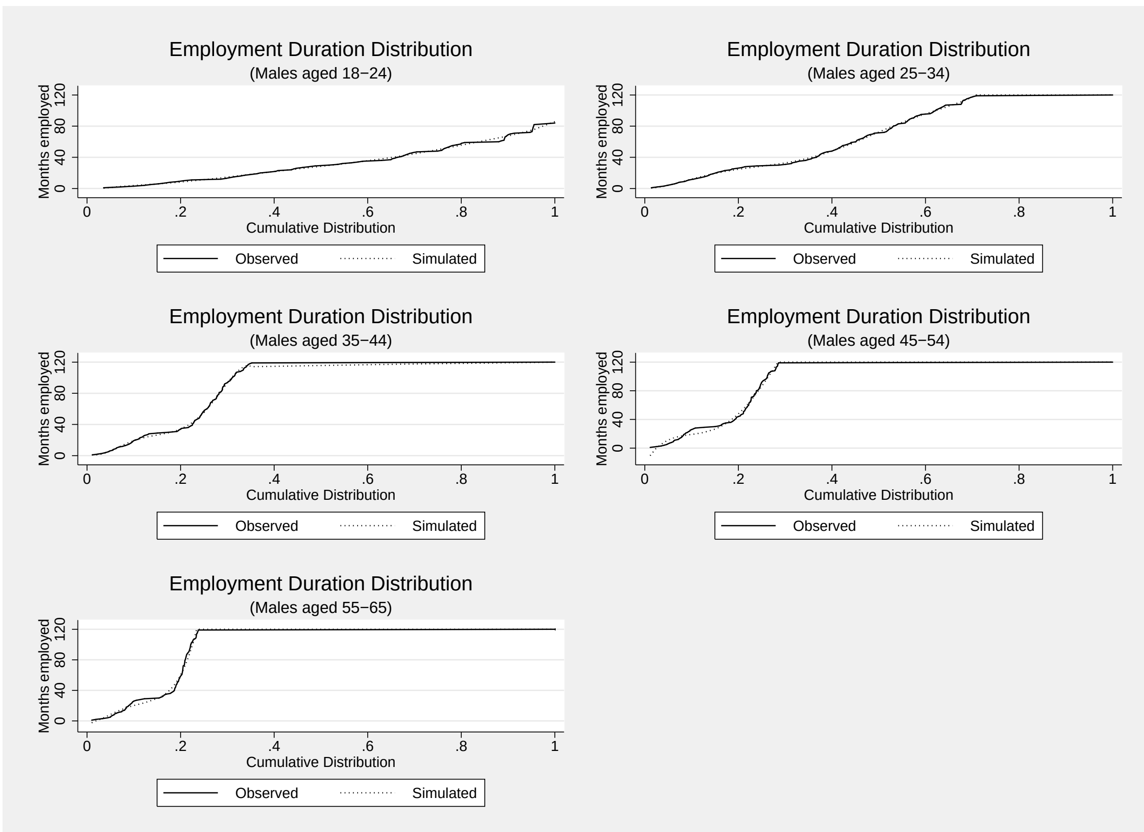
Source: Authors' own calculations based on Casen2006.

Figure 10: Job tenure for Females



Source: Authors' own calculations using EPS 2002 and 2004.

Figure 11: Job tenure for Males



Source: Authors' own calculations using EPS 2002 and 2004.

Figure 12: Debt at Risk Simulations at different DSR cut-levels

(Unemployment shift of 5%)