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How unemployment insurance savings accounts affect employment duration: Evidence from Chile

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How Unemployment Insurance Savings Accounts Affect Employment Duration:

Evidence from Chile*

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Abstract. The introduction of unemployment insurance savings accounts (UISA) in Chile in October 2002 brought in more comprehensive unemployment protection while decreasing the opportunity costs of job change. Being the first to empirically investigate the effect of UISA on employment duration, this paper examines (i) whether the introduction of UISA affected employment duration among formal private sector workers, and (ii) the magnitude of this effect. The analysis is performed on longitudinal social protection data and uses survival analysis techniques, including non-parametric, semi-parametric and parametric analysis, and competing-risk models. The paper finds that workers participating in the scheme show an increased hazard ratio of leaving employment, or accelerated time to employment termination. The effect is larger for workers becoming unemployed or inactive compared to workers changing jobs. The results provide strong support that the introduction of UISA led to shorter employment duration and higher mobility of the workforce in Chile.

Keywords: Unemployment Insurance Savings Accounts, Employment Duration, Survival Analysis, Chile
JEL classification: C41, J63, J64, J65

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1 Introduction

The introduction of unemployment insurance savings accounts (UISA) in October 2002 changed labour market conditions for formal private sector workers in Chile. Before the introduction, unemployment protection was limited to severance pay in case of job termination due to economic necessities of the firm. Additionally, high opportunity costs were involved in job change, and employers had to deal with rigid labour market regulations. After the introduction of UISA, the amount of benefits transferred to workers in case of unemployment or inactivity increased, and opportunity costs of workers changing employment decreased, while ad hoc obligations of employers to lay off workforce were reduced.

While incentives to leave unemployment have been studied in this context (Reyes, van Ours, & Vodopivec, 2010), this study is the first to empirically investigate the effect of UISA on employment duration. In this paper I fill the gap by using longitudinal social protection data containing information of employment duration of formal private sector workers before and after the introduction of the policy. The paper examines (i) whether the introduction of UISA affected employment duration among formal private sector workers, and (ii) the magnitude of this effect. Following the policy introduction, I expect that workers reacted to the changes by reduced employment duration.

I conduct an empirical analysis using survival analysis techniques to analyse employment duration: in the first part of the analysis I focus exclusively on the failure of the employment relation: if the current employment relation was terminated, irrespective of the event that follows. In the second part I apply a competing-risk model, where the different following events after employment termination are taken into account.

The results confirm that workers participating in the scheme show an increased hazard ratio of leaving employment, or accelerated time to employment termination, suggesting shorter employment duration and higher mobility of the workforce: they have a higher hazard of leaving employment in the Cox model, or accelerated time to failure in the parametric analysis, with this effect being statistically significant throughout the analysis. In the competing-risk analysis, the outcome is equally significant if the following event is another employment relation or unemployment, and for the final regression model in the case of inactivity. The effect is larger for workers becoming unemployed or inactive compared to workers changing jobs.

The paper is organized as follows: After the introduction, section 2 describes the Chilean UISA scheme, followed by a literature review on severance pay and labour mobility in section 3. Section 4 specifies the database used for the analysis, including descriptive statistics of relevant variables. Section 5 describes the method used for the analysis. In section 6 I apply survival analysis techniques for the empirical analysis: I start with non-parametric analysis using the Kaplan-Meier estimator, continue with the semi-

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parametric Cox model and parametric models, before finalizing the analysis with competing-risk models where three different possible endpoints are taken into account. The final section concludes.

2 The Chilean UISA Scheme - What has Changed?

Before the introduction of UISA, severance pay[1] was the principal form of unemployment protection in Chile for workers dismissed due to Labour Code 161,[2] complemented by benefits financed by Social Security. This implied restricted financial support during unemployment spells, as only workers who lost their employment before the expiration of the contractual agreement due to economic or other needs of the firm received benefits, without guarantee of payout of the severance liabilities, as firms tried to evade the payment or were financially unable to transfer the amount. The complementary benefits by the Social Security were minimal and independent of previous salaries.[3] Severance pay also led to inflexible labour markets, making it difficult for firms to adjust their workforce in times of economic constraints, or during a firm crisis due to high payment obligations. In addition, workers lost their accumulated rights to severance pay in case of job change leading to high opportunity costs. In October 2002 the new unemployment policy was implemented as a reaction to the previous unsatisfactory situation of formal private sector workers (Acevedo, Eskenasi, & Pagés, 2006).

Unemployment protection changed from Social Security into individual savings accounts backed up by a solidarity fund (SF). For employees with a permanent contract contributions are financed by both workers and employers, and are split between the individual accounts to save up for possible unemployment spells and the SF. The latter is also co-financed by the government (Reyes, van Ours, & Vodopivec, 2010) and presents the insurance part of the scheme. For employees with a temporary contract only the employer contributes to the savings account and workers do not have access to the SF.[4, 5]

Transfers were considerably extended in terms of eligibility and total amount transferred. The transfer of benefits was extended to workers terminating their employment for just cause,[6] conditional that they worked for a pre-defined amount of time: six months for workers with temporary contracts and twelve months for workers with open-ended contracts, continuous or discontinuous. Workers receive access to their individual savings accounts when terminating employment, and are better protected compared to the

[1] For each completed year of employment, workers are entitled to one month severance pay with a maximum of eleven years.
[2] Article 161 of the labor code: dismissal due to company needs (economic reason or downsizing).
[3] Benefits were indexed to the minimum wage to reflect purchasing power; the observed minimum wage growth was however always below the average wage growth within the economy. This resulted in decreasing replacement rates over time: from 14.8 percent in 1985 to 6.3 percent in 1995 to 4.4 percent in 2001. Replacement rates increased to over 30 percent after UISA introduction compared to Social Security benefits (Ferrada, 2010).
[4] Since a reform in May 2009 workers with temporary contracts are also eligible to receive unemployment benefits through the solidarity pillar.
[5] Appendix A includes two figures with an overview of the Chilean UISA scheme.
[6] Just causes include: expiration of contract, voluntary resignation, or misconduct.

previous state. Workers with open-ended contracts losing their job due to Labour Code 161 are equally better protected, as they have, apart from their accumulated savings, access to the solidarity fund in case of low individual savings and therefore access to the insurance component of the scheme. Although the previously existing unemployment subsidy lasting for twelve months was replaced by the savings accounts with transfers lasting for a maximum of five months, the current support system is more generous, translating into overall higher transfers. Finally, workers who do not become unemployed during their working life receive their accumulated account balance when retiring (Sehnbruch, 2004). Since the labour reform of October 2002, severance pay continues to be paid out in case of dismissal for unjust cause, with the possibility of deducting accumulated savings from the severance liabilities, improving the situation of employers.

Table 1 - Benefit changes before and after UISA introduction

EVENT	Before UISA	After UISA
Job change	Loss of accumulated rights to severance pay	Loss of severance pay (as before), keeps accumulated savings
Unemployment	Severance pay if job loss occurred due to Labour Code 161 All other cases: nothing	Severance pay (as before), transfer of accumulated savings (maximum five months), solidarity fund if applicable
Inactivity	Nothing	Transfer of accumulated savings (maximum five months)
Retirement	Nothing	Transfer of accumulated savings given account balance is positive
Death	Nothing	Transfer of remaining savings given account balance is positive to surviving dependents

Source: by author based on Acevedo, Eskenasi, & Pagés (2006).

3 Severance Pay and Labour Mobility - What do We Know?

Severance pay is a widespread form of unemployment protection, particularly in developing countries (Vodopivec M. , 2004; 2009) due to large informal labour markets and limited administrative capacities to introduce unemployment insurance (Holzman, Pouget, Vodopivec, & Weber, 2011). Severance pay is however often criticized and considered an inappropriate option for income protection. While severance pay intends to provide compensation for job loss, and to stabilize the economy by discouraging layoffs and encouraging long-term work relations, it often provides workers with limited protection during unemployment spells and distorts the behaviour of workers and firms (Feldstein & Altman, 2007; Hopenhayn & Hatchondo, 2012). High unemployment protection can have negative effects on both worker separation and accession, and consequently on labour turnover and mobility.[7] Severance pay increases firing costs and reduces consequently the probability that workers become unemployed, but also hinders job creation (Blanchard, 2000) and decreases the dynamics of structural change due to reduced mobility of the workforce (Calmfors & Holmlund, 2000). A number of studies additionally confirm the link between higher job security and lower employment levels.[8] In the case of Chile the existence of severance pay resulted in higher formal employment and increased protection rights for older and high-skilled workers, while it reduced labour market opportunities for younger and unskilled workers in the period from 1960 to 1998 (Montenegro & Pagés, 2004).[9]

Empirical papers on the effects of UISA on the transition from severance pay to UISA, and particularly on changes in workers' behaviour are still rare and many researchers have relied on simulations instead.[10] One empirical paper by Kugler (2002) documents the transition from severance pay to UISA in Colombia in 1990. Results show that although UISA partly substitute employer insurance with self-insurance in form of lower wages, the scheme smoothes consumption for the unemployed. The introduction of UISA also reduces distortions in the labour market by increasing both hiring and dismissals, and leads to higher labour mobility. In the case of Chile, a number of papers have analysed the transition in a more general context: Acevedo, Eskenasi, & Pagés (2006) discuss the political, social, and economic situation in which this programme was implemented and assess the challenges. Sehnbruch (2004) concentrates on embedding the new Chilean unemployment scheme into the context of Latin American labour market legislation, while Sehnbruch (2006) examines how the scheme works in practice and whether it can serve as a model for other emerging and developing economics. Berstein, Fajnzylber, & Gana (2012) analyse the Chilean UISA scheme as a whole and provide an overview of outcomes and reforms since its implementation.

The effect of UISA on employment duration (and consequently on labour mobility) for Chile is hitherto unclear and provides little evidence: while Berstein, Contreras & Benvin (2008) show that formal private sector workers value the new unemployment benefits more than its cost,[11] limited knowledge about UISA and its design could however work against a change in labour mobility (Poblete, 2011). A first study by Reyes (2005) on duration of employment contracts using life tables suggests that workers participating in UISA show shorter employment duration with 33 per cent "surviving" the first year of employment,

[7] Cross-country evidence, among others: Boeri & Garibaldi (2009), Gomez-Salvador, Messina, & Vallanti (2004), Messina & Vallanti (2007).
[8] Among others: Haffner et al. (2001), Heckman & Pagés (2000), Haltiwanger, Scarpetta and Vodopivec (2003).
[9] For a more extensive literature overview on severance pay, see also Holzman et al. (2011).
[10] Among others: Feldstein & Altman (2007), Fölster (1999; 2001), Vodopivec (2010).
[11] They value the benefits to different extent, depending on risk aversion, gender and educational level, but always equal or more than its costs. The authors conduct an evaluation of worker's lifetime utility with and without UISA: lifetime consumption preferences of individuals are described with a constant absolute risk aversion (CARA), allowing them to smooth consumption while economically active.

compared to 52 per cent for workers not participating. The author then focuses on workers below the age of 30 to reduce selection bias and finds that workers participating in UISA still show a difference of 7 percentage points compared to workers not participating. In his paper the author uses a different database[12] and concentrates specifically on methodological issues to assess this question.

4 Database and Descriptive Statistics

The panel database used for this analysis is the Chilean EPS database,[13] a longitudinal survey with questions on the individual and household level about the Chilean labour market and social protection system. The survey was conducted in 2002, 2004, 2006 and 2009 and contains retrospective data since January 1980. The data can be matched by a unique identifier to create a panel.[14]

The database is described as follows: The first round was conducted in 2002, and was drawn from a frame of 8.1 million current and former members of the Chilean pension system included for at least one month in the timeframe 1980-2001 containing 17,246 individuals, 937 of them reported by surviving relatives. The survey was extended in 2004 with non-participating individuals, completing the base sample, and has been since then representative on the national and regional level for the entire Chilean population. Since 2004 the data is linked to the administrative records of the pension scheme, health insurance, Chile Solidario and other welfare programmes. In 2004 new health and wealth questions were added to the questionnaire. In 2006 and 2009 the sample was kept, and includes approximately 16,000 individuals (15 years and older) of all regions.[15]

The EPS is the first panel survey conducted in Chile with four rounds of data collection covering this range of thematic areas. The questionnaires remain approximately stable over the survey rounds, containing questions on labour history and provisional systems, additional information on education, health, social protection, labour training, property and patrimony, family history and housing. This survey format allows studying the impact of different governmental programmes which have been implemented over the past three decades.

For the analysis I focus on specific variables of the EPS database: the dependent variable is length of employment duration for private sector workers measured in months, the main independent variable participation in the UISA scheme. Further explanatory variables included are *general information of the worker*: gender, age, education, risk aversion, household size, working household members, civil status,

[12] Database used: Administrative records of the contribution history and benefits paid to the workers participating in the unemployment benefit programme by the Superintendencia de Pensiones.
[13] Encuesta de Protección Social in Spanish, or social protection survey.
[14] The survey is conducted by the Centre for Microdata, Department of Economics, of the University of Chile (Centro Microdatos, Universidad de Chile) with the support of the University of Pennsylvania.
[15] In each survey round three different types of questionnaires account for repeated, new and deceased participants.

children, and w*ork related information of the worker*: contract type, hours worked per week, monthly net income, firm size, region of employment, and knowledge of UISA.[16]

The database for the analysis consists of 2,323 employment relations of dependent private sector employees: 1,489 employment relations started in the year before the policy introduction, between October 2001 and September 2002, and workers do not participate in the UISA scheme. 834 employment relations started in the year after the policy introduction, between October 2002 and September 2003, and workers compulsorily joined the new unemployment scheme. Although the complete database consists of approximately 16,000 individuals, I selected formal private sectors workers of 18 years and older who started employment in the year before and after UISA introduction into the sample for this analysis, leading to a reduced database of 2,323 employment relations, and 1,848 individuals.

Table 2 reports longer employment duration for workers not participating in the UISA scheme. This result can be however misleading, as these workers started employment in the year before the workers participating in the scheme. Additionally, 343 observations are censored, therefore still ongoing at the moment of the last survey round, leading to an expected downward bias of the estimated mean. Some individuals were also observed more than once, if they ended their employment within the considered time frame and started a new employment, and cannot be considered independent observations.[17]

Table 2 - Average employment duration

UISA	Months	St. Err.	[95% Conf.	Interval]	Freq.
Before	31.9	0.80	30.37	33.50	1,489
After	22.8	0.87	21.04	24.47	834
Total	28.6				2,323

For the competing-risk analysis, I additionally take the following event into account, after finishing the initial employment relation. For workers who ended their employment within the survey rounds, the distribution of the following event is divided into: 798 individuals changed into a new employment, 864 became unemployed, and 318 became inactive. The following event is approximately equally distributed between change in employment, and unemployment with ca. 40 per cent for each event. Slightly more

[16] Summary statistics of all variables in appendix B.
[17] Repeated spells: throughout the analysis I run the regressions by clustering the observations by their unique identifier. By specifying clusters the single observations are not considered independent, but the clusters defined. Due to repeated spells in the data set, I clustered the ID of the observations, as the same worker can be observed more than once since more than one job can be started during the two year period considered. It is reasonable to assume independence of individuals, but not within different observations of the same individual. The data set contains 2,323 observations and 1,848 individuals. Specifying the ID clusters in the regressions, I obtain robust standard errors. In case of observing intra-cluster correlations, the robust standard errors are better indicators for estimator variability, resulting in more accurate outcomes.
Models with individual-level frailties (random-effect models in survival analysis) did not converge.

workers face unemployment after terminating their current employment relation, compared to a new employment contract. Inactivity is observed among 16 per cent of the workers.

5 Method - Survival Analysis

I conduct the analysis using survival analysis techniques, also known as event history or duration analysis. It is defined as the analysis of time until the occurrence of a specific event, from a pre-defined starting point to the transition from one state to another, conditional that it has not yet occurred. In this analysis the time of interest is represented by the duration in one specific employment relation, the event of interest represented by terminating this employment period. Workers are throughout time 'at risk' of terminating employment and experiencing the failure event (Box-Steffensmeier & Jones, 2004).

Survival analysis is different from Ordinary Least Square (OLS) regressions for a number of reasons and requires a special framework: first, the normality distribution of residuals cannot be assumed, as normality of time is unreasonable for many events. The risk of the event occurring is generally not constant over time and almost certainly non-symmetric (e.g. bi-modal). Second duration, or time to failure, is always positive. And third it encounters the problem of right censoring: the observed individual participates in the survey, but the event might not have yet occurred when the survey finishes. In this case the policy was introduced in October 2002, and the last survey round available records data until early 2010. The workers remaining in their current employment are no longer observed until the following survey round is conducted and published, and are censored. In the analysis I assume non-informative censoring meaning that the censoring time of an individual tells nothing about the risk after that time.

There are three main approaches in survival analysis: non-parametric analysis, the semi-parametric Cox proportional hazards (PH) model and parametric models. While non-parametric and semi-parametric models compare subjects at the time when failures actually occur, parametric models use probabilities that describe what occurs over the whole interval given the information of the subject during time x_j (Cleves, Gutierrez, Gould, & Marchenko, 2010). To be more specific: non-parametric analysis assumes no functional form of the survivor function and makes therefore no assumption about the hazard or cumulative hazard, so 'letting the data set speak for itself'. The effects of additional sets of covariates are not modelled either, and the comparison is performed on a qualitative level. In the semi-parametric Cox model the parametric shape is equally left unspecified, but the model assumes that covariates have proportional baseline hazards. Parametric models are either written as linear regressions, in the hazard parameterization, or in the log-time parameterization, also known as accelerated failure time (AFT) metric. All parametric models make assumptions about the shape of the hazard function, with the simplest being the exponential model assuming a constant hazard over time. Further models include Weibull or

Gompertz distributions (flat, monotonically increasing or decreasing hazard rates), log-normal and log-logistic models (non-monotonic hazard rates) and the flexible three-parameter generalized gamma distribution (Cleves, Gutierrez, Gould, & Marchenko, 2010).

Estimates are obtained by calculating the maximum likelihood for parametric, and by calculating the partial likelihood for semi-parametric models. Breslow or Efron approximations are used to compute the partial likelihood in case failure events are tied in the data set. The maximum likelihood function assuming non-informative censoring includes censored observations with survival time t_i and failure indicator d_i (taking the value 1 for failures and 0 for censored observations) and has the form

$$L = \prod_{i=1}^{n} S(t_i|x_i, \beta)\ \lambda\left(t_i\middle|x_{i,\beta}\right)^{d_i} \tag{1}$$

and the partial likelihood with k distinct observed failure times and no ties

$$L = \prod_{j=1}^{k} \left\{\frac{\exp\left(x_j\beta_x\right)}{\sum_{i\epsilon R_j} \exp\left(x_j\beta_x\right)}\right\} \tag{2}$$

(Cleves, Gutierrez, Gould, & Marchenko, 2010) and (Rodríguez, 2010).

In a first step, I estimate the survivor function without assuming any particular functional form. The Kaplan-Meier estimator, a non-parametric estimator of the survivor function S(t), estimates the probability of survival past a certain time t and is given by

$$\hat{S}(\mathrm{t}) = \prod_{j|t_j \le t} \frac{n_j - d_j}{n_j} \tag{3}$$

where n_j represents the number of individuals at risk at time t_j and d_j represents the number of failures at time t_j. This stepwise function shows the survival of workers in their employment, presenting first results of survival between workers who are participating in the UISA scheme compared to those who are not.

In a second step, I analyse the survival of employment using the semi-parametric Cox model. The Cox proportional hazards model (Cox, 1972) and (Cox, 1975) is given by

$$\lambda\ (\mathrm{t}|x_j) = \lambda_0(\mathrm{t})\ \exp(x_j\beta_x) \tag{4}$$

where λ_0(t) is the baseline hazard and $x_j\beta_x$ the covariates and regression parameters. The baseline hazard is not given a particular parametrization and is left unestimated. The model makes no assumption about the hazard shape over time, but all individuals are assumed to have the same hazard over time, meaning that the hazard rate for any two individuals at any point in time is proportional (Cleves, Gutierrez, Gould, & Marchenko, 2010).

In a third step, I select a functional form for the hazard rate using the Akaike Information Criterion (AIC) and parameterize the shape of the hazard function. Parametric estimations use probabilities that describe the data over the whole time interval given what is known about the observations during this time.

Parametric models are written in two different ways:

in the hazard metric,

$$h(t|x_j) = h_0(\mathrm{t}) \exp(x_j\beta_x) \tag{5}$$

in the log-time metric, also known as the AFT metric,

$$\ln(t_j) = x_j\ \beta_x + \in_j. \tag{6}$$

Hazard parameterizations can fit exponential, Weibull and Gompertz distributions. Widely used log-time parameterizations are exponential, Weibull, log-normal, log-logistic and the generalized gamma distribution (Cleves, Gutierrez, Gould, & Marchenko, 2010).

In a fourth and final step, I apply a competing-risk model to the data, where the endpoint consists of several distinct events and the failure can be attributed to one event exclusively to the others. In a competing risk model I am interested in the cause-specific hazard function:

$$\lambda_j\ (\mathrm{t}) = \lim_{\Delta\to 0+} \frac{P(t\leq T<t+\Delta t|T\geq t)}{\Delta t} \tag{7}$$

where λ_j indicates the hazard rate for a single-state process where the hazard rate is subscripted for each of the j events that can occur. To conduct the analysis I censor all events, but the event of interest. Each part of the product can be then estimated separately and I obtain risk-specific hazard rates. As before, I can equally conduct non-parametric, semi-parametric and parametric analysis.

6 Empirical Analysis

The main results of the empirical analysis can be summarized as follows: in the first part of the analysis I focus exclusively on the failure event of terminating the current employment. UISA participation is significant and increases the hazard of leaving employment, or accelerates time to failure, throughout all regressions irrespective of the method selected or the covariates included in the regressions. In the second part of the analysis, results are qualitatively comparable if the following event is a new employment relation or unemployment: UISA participation is significant throughout all regressions. This is however not the case for workers becoming inactive after terminating their current employment: the difference between both groups is not significant for the Kaplan-Meier estimator, the simple regression or the base specification. Only in the final model UISA participation becomes significant. Quantitatively the effect is larger for workers becoming unemployed or inactive, compared to workers changing employment.[18]

6.1 Non-Parametric Analysis

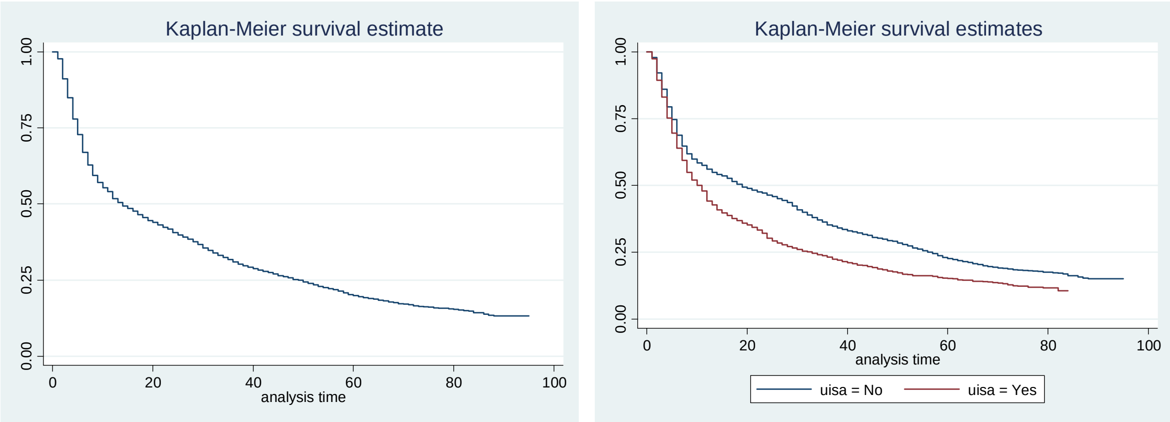
I start the empirical analysis with the Kaplan-Meier (KM) estimator: figure 1 (a) plots the overall Kaplan-Meier survival estimate, and figure 1 (b) by UISA participation. Figure 1 (a) shows a high hazard rate of employment termination during the first year of employment: after approximately twelve months, half of all workers have terminated their current employment contract. From twelve to approximately 42 months another quarter of workers terminate employment. Afterwards the number of surviving workers continues declining in a steady and moderate pace, until the final survey round finishes and approximately 15 per cent of the sample is still employed and therefore censored. In figure 1 (b) survival is similar during the first months of employment and starts diverging after approximately ten months, showing higher employment survival for workers not participating in the UISA scheme. The logrank and the Wilcoxon test confirm that the estimates are significantly different: with a p-value of 0.000 the logrank test rejects the null hypothesis that both estimates are equal and concludes that the difference in employment survival is statistically significant. Returning a p-value of 0.000, the Wilcoxon result equally rejects the null-hypothesis.[19]

[18] In addition to the continuous time analysis, I run the regressions based on discrete time analysis and use the complementary log-log regression (the discrete-time proportional hazards model) to compare if results are similar: the cloglog regressions return qualitatively comparable results, where the UISA variable is statistically significant at a 1 percent level throughout the regressions and equally increases the hazard of leaving employment. Coefficients are quantitatively above the results of continuous time analysis, the difference is however minor.

[19] With the logrank test I test the null hypothesis that the probability of employment survival of both groups is the same at any point of time. It compares the survival of both groups by taking the follow-up period into account (Bland & Altman, 2004). The Wilcoxon test is a rank test which places additional weight to earlier failure times than failures later in the distribution compared to the logrank test. In case the hazard functions are not proportional, this test is preferred over the logrank test (Cleves, Gutierrez, Gould, & Marchenko, 2010). I conduct both tests, as the proportionality assumption has not yet been tested.

Figure 1 - KM survival estimates

(a) overall **(b)** by UISA



6.2 Semi-Parametric Cox Model

Simple Cox Regression

I continue with the simple Cox model, where I regress the main independent variable UISA on employment duration. The result in table 3 returns a coefficient of 0.273. Expressed in hazard rates the hazard of leaving employment is approximately 1.314 times higher for workers participating in the UISA scheme (hazard increases by 31.4 per cent) and is statistically significant at the 1 per cent level.

Next, I test the PH assumption of the simple Cox model. I start with a graphical analysis and plot the hazards of both groups. The hazards are estimated over the range of observed failure times, and all failure times contribute to the estimate of the baseline hazard. The hazard ratios depicted in the figures are approximately proportional:

Figure 2 - Estimated baseline hazards

(a) Epanechnikov kernel **(b)** Gaussian kernel

I also conduct a formal test based on Schoenfeld residuals. This test retrieves the residuals, fits a smooth function of time to them, and tests whether there is a relationship. For this test time is log-transformed. The result p = 0.441 suggests that there is no evidence of non-proportionality. I do an additional formal test by introducing an interaction between the UISA variable and time. For the test time is log-transformed and the result (p = 0.427) equally suggests that there is no evidence that the UISA effect changes with ln(time).

Multiple Cox Regression

I start the multiple Cox regressions by specifying a base specification. I expect the following variables to have an effect on the decision of remaining in employment: gender, age, contract type and education. Education is split into four dummy variables: basic education (the reference category), high school, professional formation and higher education (university and higher). All variables are statistically significant at the 1 per cent level, except for age significant at the 5 per cent level. The education dummies are collectively significant at the 1 per cent level. While UISA participation, female, and a temporary contract increase the hazard of leaving employment, the hazard decreases with age and a higher educational level. With a coefficient of 0.282 the effect of the UISA variable is similar to the simple regression, translating into a hazard ratio of 1.327, or a 32.7 per cent increase in the hazard of terminating employment.

Afterwards I test additional sets of covariates. First I add average net income, total hours worked per week and number of workers per firm to capture information on type, place and quality of work. Second individual risk aversion,[20] third number of household members, working household members, civil status[21] and number of children to capture information on the household composition, fourth region of work captured by a dummy variable indicating if the worker lives in the metropolitan region of Santiago, and fifth knowledge of the UISA scheme. Income is split into five dummy variables: zero income (the reference category), income up to 100,000 CLP, between 100,000 and 200,000 CLP, between 200,000 and 300,000 CLP, and above 300,000 CLP.[22] UISA participation, gender, and contract type remain statistically significant throughout all regressions, while age and education vary over the regressions. The coefficient of UISA almost doubles after including the income dummies, increasing the effect of UISA participation when income is hold constant. Throughout all regressions, income is collectively significant at the 1 per cent level. Hours worked per week is significant at the 5 per cent level, while firm size, individual risk aversion, working household members, civil status, number of children, region and

[20] Risk aversion measured by asking survey participants about their individual risk assessment on a scale from 0 (for individuals considering themselves as highly risk averse) to 10 (for individuals stating they are highly disposed to take risk).
[21] If married (includes cohabiting).
[22] On 16 July 2013: 1 Euro = 660 CLP [www.xe.com].

knowledge of UISA are not significant. Although household size is not significant in the Cox model, I decide to keep this variable as it becomes significant in other regressions. Regression (8) in table 3 presents the final Cox model, including all variables of the base specification, hours worked, average net income and household size. The UISA coefficient increases to 0.517 in the final model, translating into a hazard ratio of 1.677, or a 67.7 per cent increase in the hazard of terminating employment.

Finally, I test a number of interaction terms in regression (9).[23] The following interaction terms are significant: UISA x contract type, and UISA x education dummies. Having a temporary contract and participating in the UISA scheme additionally increases the hazard of terminating employment, above and beyond the single effects of the variables. For the other interaction term, UISA x education dummies, the hazard decreases with higher education if workers participate in the UISA scheme.[24, 25]

[23] Interactions tested:
UISA*Female, UISA*Age, UISA*Temp.Contract, UISA*Education Dummies, UISA*Income Categories, UISA*Household Size, Female*Age, Female*Temp.Contract, Age*Temp.Contract, Temp.Contract*Hours, Temp.Contract*Income Categories, Temp.Contract*Household Size.

[24] In addition to this sample, I run the regressions with an extended sample including workers who started two years before and two years after the UISA introduction. Regression results are discussed in appendix E.

[25] As control group I take a sample including public sector employees and separate the sample by workers starting in the year before and after UISA introduction in October 2002. Compared to the sample with formal private sector workers, this sample does not show statistically significant results in "UISA participation". Regression results are discussed in appendix F.

Table 3 - Regression table Cox model

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Coefficients				
UISA	0.273***	0.282***	0.513***	0.511***	0.539***	0.516***	0.517***	0.517***	0.588***
- UISA marg. effect									0.491***
Female		0.293***	0.202***	0.212***	0.219***	0.203***	0.201***	0.203***	0.171***
Age		-0.005**	-0.004*	-0.004	-0.005*	-0.005**	-0.005**	-0.005**	-0.005**
Temp. Contract		0.987***	0.916***	0.912***	0.922***	0.923***	0.912***	0.912***	0.758***
Education									
- High School		-0.207***	-0.140**	-0.149**	-0.131**	-0.147**	-0.148**	-0.150**	0.004
- Prof. Formation		-0.238***	-0.109	-0.119	-0.099	-0.105	-0.099	-0.101	0.131
- Univ. and higher		-0.444***	-0.201	-0.201	-0.153	-0.209*	-0.211*	-0.211*	-0.016
Hours			0.007**	0.007**	0.008**	0.007**	0.007**	0.007**	0.007**
Income									
- 100,000 CLP			0.073	0.066	0.062	0.084	0.066	0.067	0.085
- 200,000 CLP			-0.200	-0.196	-0.215	-0.192	-0.202	-0.201	-0.191
- 300,000 CLP			-0.433	-0.444	-0.438*	-0.444	-0.439	-0.442	-0.431
> 300,000 CLP			-0.538*	-0.547*	-0.519*	-0.541*	-0.539*	-0.543**	-0.540*
Number of Workers			0.000						
Risk Aversion				0.006					
Household Size					-0.016	-0.019	-0.019	-0.019	-0.018
Working HH Members					-0.010				
Married					-0.027				
Children					0.028				
Metropolitan Region						0.059			
Knowledge of UISA							0.028		
UISA x Temp. Contract									0.380***
UISA x High School									-0.367***
UISA x Prof. Formation									-0.536***
UISA x Univ. and higher									-0.472**
Log Likelihood	-14,022	-13,728	-11,200	-11,199	-10,691	-11,362	-11,362	-11,362	-11,345
AIC	28, 047	27,469	22,427	22,425	21,413	22,752	22,753	22,751	22,723
Pseudo R2	0.001	0.020	0.023	0.023	0.024	0.023	0.023	0.023	0.025
Wald Test Education		0.000	0.132	0.106	0.234	0.099	0.092	0.088	0.005
Wald Test Income			0.000	0.000	0.000	0.000	0.000	0.000	0.000
Exit	1,980	1,976	1,649	1,649	1,585	1,670	1,670	1,670	1,670
At Risk	66,530	66,484	62,479	62,586	59,108	63,427	63,427	63,427	63,427
N	2,323	2,319	1,982	1,981	1,899	2,006	2,006	2,006	2,006

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

Notes: Instead of hazard ratios, coefficients are reported in this table: positive coefficients increase the hazard, negative coefficients decrease the hazard. Hazard ratios are obtained by taking the exponential of the coefficient.

Next the PH assumption is tested for the base specification, the final Cox model and the Cox model with interactions. For the Cox model to be valid and to satisfy the PH assumption, the global PH test must return p-values above the threshold of 10 per cent. The global PH test reports for the three regressions p-values of 0.000,[26] rejecting the PH assumption and making the Cox model invalid. While UISA participation and education suggest that there is no evidence of non-proportionality in the base specification, gender, age and contract type report p-values below the 10 per cent threshold. In the final Cox model various variables have low p-values: UISA participation, gender, age, contract type, and the income dummies. The results are similar for the interaction model, except for UISA participation and gender, where the p-values are above the threshold value. A stratified Cox model presents a possible solution when certain covariates do not satisfy the PH assumption (Ata & Sözer, 2007).

Stratified Cox Model

Due to the previous results, I relax the assumption that every individual faces the same baseline hazard,

$$\mathrm{h}(\mathrm{t}|x_j) = h_0(\mathrm{t}) \exp(x_j\beta_x) \tag{8}$$

in favour of

$$\mathrm{h}(\mathrm{t}|x_j) = h_{01}(\mathrm{t}) \exp(x_j\beta_x), \qquad \text{if } j \text{ is in group 1} \tag{9}$$

$$\mathrm{h}(\mathrm{t}|x_j) = h_{02}(\mathrm{t}) \exp(x_j\beta_x), \qquad \text{if } j \text{ is in group 2} \tag{10}$$

The baseline hazards can now differ across the levels of stratified variables, but the coefficients β_x continue to be the same (Cleves, Gutierrez, Gould, & Marchenko, 2010). Covariates returning high p-values are assumed to satisfy the PH assumption and are included in the model, while covariates that do not fulfil this criterion and report low p-values are stratified (Ata & Sözer, 2007).

I apply the stratified model to the data: after testing different sets of stratified regressions, I stratify contract type in the base specification, and age, contract type and hours in the final model and the interaction model. The global PH tests return a p-value of 0.182 for the base specification, a p-value of 0.813 for the final model and a p-value of 0.717 for the interaction model, rejecting the evidence of non-proportionality. Using the stratified Cox model is therefore more appropriate for the data. The coefficients of UISA participation remain similar, therefore suggesting quantitatively comparable effects compared to the previous Cox regression table.[27]

[26] See table 8 in appendix C.
[27] See table 10 in appendix D.

6.3 Parametric Models

I start the parametric analysis by comparing the six parametric model shapes using the Akaike Information Criterion. The AIC penalizes each model's log likelihood to reflect the number of parameters estimated (Akaike, 1974). The preferred model distribution is the one with the lowest AIC value, in my case the generalized gamma distribution. Using this distribution, I run four regressions (simple model, base specification, final model and interaction model) and compare the results in table 4: the UISA variable is statistically significant at the 1 per cent level in all regressions, as well as age, contract type, hours worked and income. In all four regressions the UISA coefficient is negative, implying "accelerated" time to failure. Expressed as time ratios, the simple model returns a value of 0.781, suggesting that time to failure is approximately 21.9 per cent lower compared to workers not participating in the scheme. In the base specification time to failure is less accelerated for UISA participants with a time ratio of 0.850. When adding the income variables to the regressions in the final and interaction model, the UISA coefficient value decreases. The results returns a time ratio of 0.627 and 0.628 (marginal effect), respectively. Education is not significant in the final model, while income is significant at the 1 and 10 per cent level in the base specification and the interaction model, respectively. The interaction terms are significant at the 5 per cent level, and confirm the previous interpretation: participating in the UISA scheme and having a temporary contract additionally accelerate time to failure, while the interaction UISA x education decelerates time to employment termination. Analysing the parameters, the special cases of the generalized gamma distribution Weibull ($\kappa = 1$), log-normal ($\kappa = 0$) and the exponential distribution ($\kappa = \sigma = 1$) are not fulfilled.

Table 4 - Generalized gamma regressions

VARIABLE	Simple Model	Base Specification	Final Model	Interactions
	Acceleration Parameters			
UISA	-0.247***	-0.162***	-0.467***	-0.567***
- UISA marg. effect				-0.465***
Female		-0.239***	-0.179***	-0.157**
Age		0.010***	0.008***	0.009***
Temp. Contract		-1.305***	-1.203***	-1.080***
Education				
- High School		0.146**	0.068	-0.066
- Prof. Formation		0.218**	0.042	-0.125
- Univ. and higher		0.481***	0.141	-0.017
Hours			-0.011***	-0.011***
Income				
- 100,000 CLP			0.095	0.133
- 200,000 CLP			0.453**	0.493**
- 300,000 CLP			0.745***	0.772***
> 300,000 CLP			0.901***	0.934***
Household Size			0.026*	0.026*
UISA x Temp. Contract				-0.294**
UISA x High School				0.331***
UISA x Prof. Formation				0.422**
UISA x Univ. and higher				0.398
_const	2.270***	2.919***	3.258***	3.282***
/ln_sig	0.306***	0.221***	0.206***	0.199***
/kappa	-0.897***	-0.371***	-0.235***	-0.191**
sigma	1.358	1.247	1.228	1.220
Log Likelihood	-3,873	-3,575	-3,024	-3,015
AIC	7,754	7,170	6,081	6,070
Wald Test Education		0.000	0.678	0.059
Wald Test Income			0.000	0.000
Employment Exit	1,980	1,976	1,670	1,670
At Risk	66,530	66,484	63,427	63,427
N	2,323	2,319	2,006	2,006

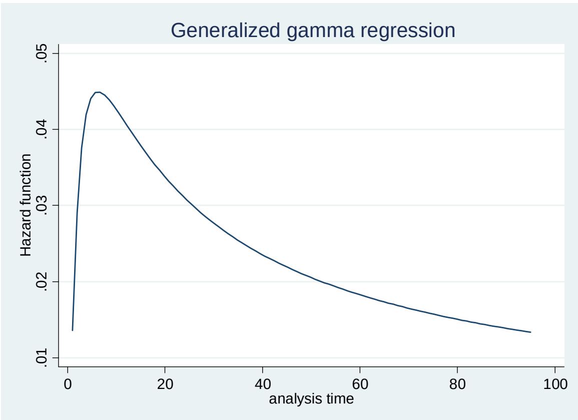
* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

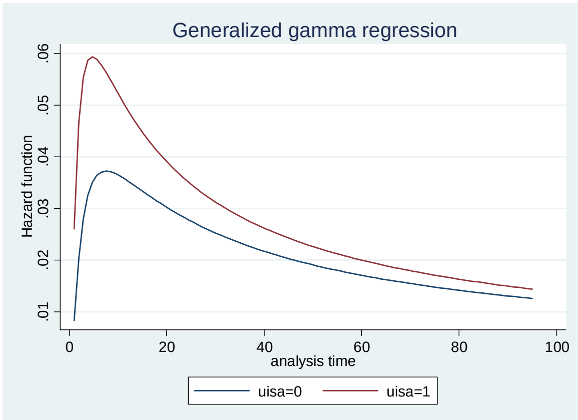
Notes: The coefficients reported in table 4 are expressed as $\tau_j = \exp(-x_j \beta_x) t_j$ and are called the acceleration parameters. If coefficients are negative, they "accelerate" time, so failure is expected to occur sooner; if coefficients are positive, they "decelerate" time, so failure is expected to occur later. If coefficients are equal to zero, then time passes at its "normal" rate (Cleves, Gutierrez, Gould, & Marchenko, 2010). Another option are exponentiated coefficients, which are interpreted as time ratios.

As a last step in the parametric analysis, I run the final model, and estimate the hazard functions based on the generalized gamma distribution.[28] Figure 3 (a) returns the overall hazard, indicating a steep increase in the hazard rate during the first year of employment, with a peak after approximately 12 months, and a steady decline thereafter. Figure 3 (b) shows the hazard function by UISA participation, with a considerably higher hazard rate for UISA participants, diverging especially during the first two years of employment, and converging over the remaining time. The peak after approximately one year is more pronounced for UISA participants.

Figure 3 - Hazard functions

(a) overall **(b)** by UISA





Notes: Hazard functions are performed on the final model.

6.4 Competing-Risk Model

In a competing-risk model the failure event can occur for more than one reason. In this dataset terminating employment can lead to three different events: to another employment contract (T_1), to unemployment (T_2), or to inactivity (T_3). Only one of these three possibilities can occur at once. Compared to the previous analysis, competing-risk data focuses on the cause-specific hazard function instead of the hazard or cumulative hazard function, and on the cumulative incidence function instead of the survivor function. The cause-specific hazard function describes the risk of failure from the specific event, given the failure has not yet occurred. The cumulative incidence function (CIF) is closely related to the failure function describing the probability of failing before or up to time t, but generalizes this concept to the competing-risk model. The CIF at time t for cause j is the probability of failing from the specific cause j before or up to time t. In a competing-risk model, I can equally conduct non-parametric,

[28] I concentrate on the final model, as the AIC returns only marginally lower values for the interaction model. I additionally run the hazard functions with the interactions models, and the figures return qualitatively and quantitatively similar results.

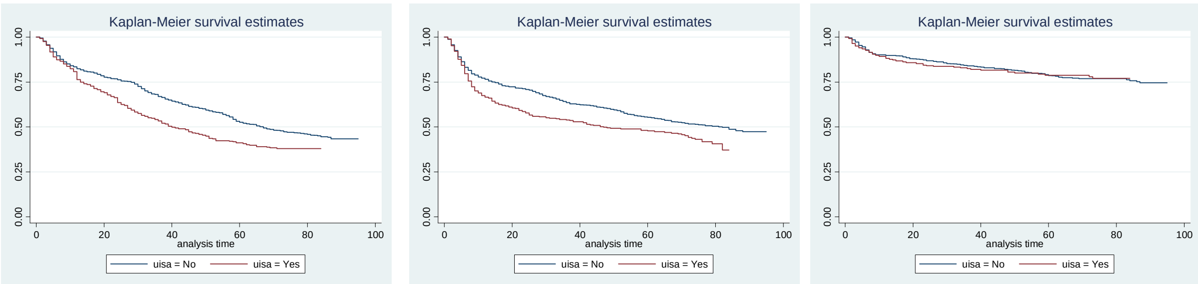
semi-parametric and parametric analysis. As before, I start with non-parametric Kaplan-Meier estimates, continue with the semi-parametric Cox model and finalize the analysis with fitting parametric models.

Non-Parametric Analysis

For figures 4 (a) and (b) the logrank and Wilcoxon test return p-values of 0.000, however not for figure 4 (c). For inactivity as the following event, the logrank test returns a p-value of 0.451, and the Wilcoxon test a p-value of 0.206, translating into no significant difference between both groups. While UISA participation makes a difference if workers change employment or become unemployed, it appears to be irrelevant for workers becoming inactive. In the first two cases the hazard ratio of UISA participants is higher compared to the workers not participating in the scheme.

Figure 4 - Kaplan-Meier survival estimates

(a) T_1 - Employment **(b)** T_2 - Unemployment **(c)** T_3 - Inactivity



Semi-Parametric Cox Model

Based on the regression table 3 of the semi-parametric analysis, I run the simple regression (1), the base specification (2) and the final model (3).[29] Different to the previous analysis, I now take into account the three different causes of employment termination. The results in table 5 vary depending on the event following employment termination. If workers change their employment, UISA participation, gender, and contract type are statistically significant variables, while age, education, hours worked, income and household size do not return significant results. If workers become unemployed all variables are significant at the 1 per cent level, except of household size. For the last option, inactivity, the picture changes over the regressions: while UISA participation does not return significant results for the simple model and the base specification, it is statistically significant at the 1 per cent level in the final model. The remaining variables are significant at the 1 or 5 per cent level, except of hours and household size.

[29] I exclude the interaction model to consolidate the competing-risk analysis.

The magnitude of the UISA effect varies according to the next event:[30] while the coefficient returns a value of 0.375, translating into a hazard ratio of 1.455 or a 45.5 per cent increase in the hazard of terminating employment when the next event is a new employment relation, the coefficient almost doubles to 0.645, translating into a hazard ratio of 1.906 or a 90.6 per cent increase in the hazard of terminating employment when the following event is unemployment. For inactivity as the next event, the coefficient returns a value of 0.504, translating into a hazard ratio of 1.655 or a 65.5 per cent increase in the hazard of terminating employment. While UISA participation has an effect on the duration of employment in all three cases and increases the hazard of terminating employment, the effect is the highest for workers becoming unemployed. The effect is also higher for inactivity compared to changing employment. A possible explanation could present the direct benefit of receiving the accumulated savings in the case of unemployment or inactivity, while a job change does not result in immediate benefits, but reduced opportunity costs.

[30] I concentrate on the coefficients of the final model.

Table 5 - Regression table Cox model

VARIABLE	T_1 - Employment			T_2 - Unemployment			T_3 - Inactivity		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	Coefficients								
UISA	0.314***	0.318***	0.375***	0.301***	0.310***	0.645***	0.090	0.050	0.504***
Female		-0.275***	-0.297***		0.363***	0.358***		1.371***	1.102***
Age		-0.004	-0.004		-0.013***	-0.013***		0.012**	0.013*
Temp. Contract		0.643***	0.642***		1.239***	1.217***		1.204***	0.849***
Education									
- High School		0.006	0.034		-0.307***	-0.276***		-0.379***	-0.294*
- Prof. Formation		0.077	0.139		-0.671***	-0.538***		0.063	0.323
- Univ. and higher		-0.069	0.003		-1.142***	-0.803***		-0.028	0.426
Hours			-0.000			0.015***			0.005
Income									
- 100,000 CLP			-0.303			0.350			0.433
- 200,00 CLP			-0.499*			0.149			-0.086
- 300,000 CLP			-0.629**			-0.099			-0.819
> 300,000 CLP			-0.576*			-0.439			-1.086
Household Size			-0.010			-0.024			-0.031
Log Likelihood	-5,556	-5,510	-5,056	-6,180	-5,940	-4,618	-2,285	-2,160	-1,588
AIC	11,114	11,033	10,139	12,363	11,895	9,261	4,572	4,334	3,201
Pseudo R2	0.002	0.010	0.012	0.001	0.035	0.045	0.000	0.055	0.056
Wald Test Education		0.859	0.804		0.000	0.000		0.013	0.008
Wald Test Income			0.112			0.005			0.000
Employment Exit	798	798	741	864	860	689	318	318	240
At Risk	66,530	66,484	63,427	66,530	66,484	63,427	66,530	66,484	63,427
N	2,323	2,319	2,006	2,323	2,319	2,006	2,323	2,319	2,006

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. adjusted clustered by ID)

Notes: Regressions (1) present the simple model, regressions (2) the base specification, and regressions (3) the final model.

I test again the PH assumption, and to consolidate the analysis, I test the assumption for the final model only. None of the regressions fulfil the PH assumption: the values returned for the global PH test are 0.000 in all cases, suggesting that hazards are non-proportional.[31] Age and contract type are stratified and the global PH test results suggest that the stratified Cox model is valid in all three cases.

The coefficients return qualitatively and quantitatively comparable results as in table 5. Irrelevant of the event following employment termination, UISA participation is positive and statistically significant at the 1 per cent level. Participating in the new scheme increases the hazard of workers leaving their current

[31] See table 9 in appendix C.

employment and is quantitatively similar to the previous Cox regressions: the hazard of terminating employment increases by 42.6 per cent if workers change their employment, by 75.6 per cent if workers become unemployed, and by 83.1 per cent if workers become inactive.[32]

Parametric Models

As a last step I fit parametric models and proceed as before. I concentrate on the final model, and test the preferred hazard shape for the different parametric models. The gamma distribution is the preferred model shape for T_1 and T_2, and the log-normal distribution for T_3. As the AIC of the log-normal distribution is only marginally below the AIC of the gamma distribution, I also use the latter shape for T_3.

In table 6 all UISA coefficients are statistically significant at the 1 per cent level. The UISA coefficients return again considerably lower acceleration parameters for unemployment and inactivity: while UISA participation accelerates failure in all cases, the effect is more pronounced if workers become unemployed or inactive after terminating their current employment. The time ratios are 0.705 for employment, 0.563 for unemployment, and 0.535 for inactivity when taking the exponentiated coefficient.

Another interesting aspect is the gender coefficient: women have a lower hazard of terminating employment if the following event is a new employment relation, but have an increased hazard of terminating employment if the following event is unemployment, and especially when becoming inactive. Education is not significant when changing job, it however decelerates time to failure when the following event is unemployment and is significant at the 1 per cent level, while the effect is the opposite for inactivity. The variable hour is only significant when the following event is unemployment and accelerates time to failure. Income is significant in all cases and decelerates time to failure the higher the income category. Household size is significant at the 10 per cent level when becoming unemployed and slightly decelerates time.

[32] See table 11 in appendix D.

Table 6 - Generalized gamma regressions

VARIABLE	T_1 - Employment	T_2 - Unemployment	T_3 - Inactivity
		Acceleration Parameters	
UISA	-0.349***	-0.575***	-0.625***
Female	0.362***	-0.375***	-1.234***
Age	0.006	0.013***	-0.007
Temp. Contract	-0.966***	-1.474***	-1.095***
Education			
- High School	-0.103	0.194*	0.254
- Prof. Formation	-0.280*	0.616***	-0.455
- Univ. and higher	-0.025	0.754***	-0.712**
Hours	-0.002	-0.019***	-0.014
Income			
- 100,000 CLP	0.484*	-0.075	-0.390
- 200,000 CLP	0.811***	0.178	0.294
- 300,000 CLP	0.980***	0.477	1.054
> 300,000 CLP	0.903***	0.891**	1.423*
Household Size	0.017	0.034*	0.036
_cons	3.163***	4.885***	7.109***
/ln_sig	0 .497***	0.465***	0.820***
/kappa	-0.624***	-0.209	-0.410
sigma	1.644	1.592	2.270
Log Likelihood	-1,913	-1,817	-876
AIC	3,857	3,666	1,783
Wald Test Education	0.362	0.001	0.003
Wald Test Income	0.002	0.001	0.000
Employment Exit	741	689	240
At Risk	63,427	63,427	63,427
N	2,006	2,006	2,006

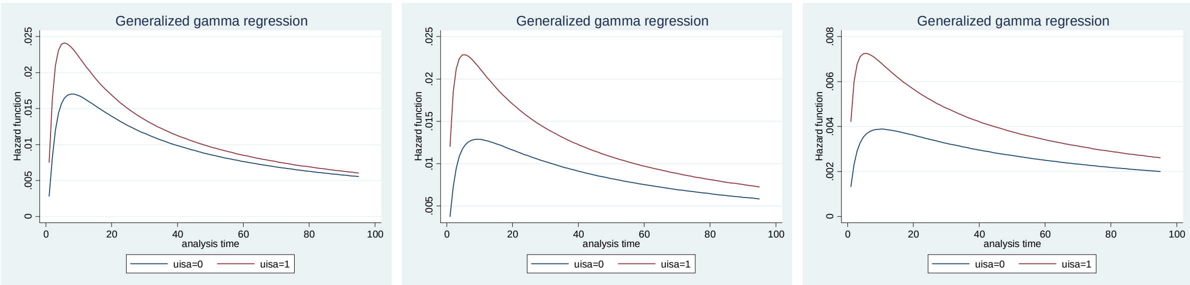
* $p<0.1$, ** $p<0.05$, *** $p<0.01$ (Std. Err. adjusted clustered by ID)

Notes: All regressions are based on the final model.

In figure 5 I compare the hazard functions by UISA participation, and in all cases UISA participants have a higher hazard of terminating employment, irrespective of the following event. The shape is comparable, with a steep hazard increase during the first months of employment, a peak after the first year, and a steady decline thereafter.

Figure 5 - Hazard functions by UISA

(a) T_1 - Employment **(b)** T_2 - Unemployment **(c)** T_3 - Inactivity



Notes: Hazard functions are performed on the final model.

7 Concluding Remarks

This paper analyses the impact of UISA on employment duration in Chile and was motivated by two questions: (i) whether the introduction of UISA has an effect on employment duration and therefore on labour mobility, and (ii) on the magnitude of this effect. Due to changes in labour market conditions, benefits increased in case of unemployment or inactivity, and opportunity costs decreased for employment change, resulting in less costly employment termination. Based on my results, I conclude that UISA participation significantly affects employment duration, characterized by an increased hazard ratio of exiting the current employment in the Cox regressions, and by accelerated time to failure in the parametric models.

In the simple Cox regression the hazard is elevated by 31.4 per cent for UISA participants, while the difference amounts to 67.7 per cent in the final model. The results of the stratified models are similar: the final model, for example, increases the hazard ratio by of 71.8 per cent. The parametric models, based on the generalized gamma distribution, return qualitatively the same result as the Cox model: time to failure is accelerated if workers participate in UISA. The time ratio returns a coefficient of 0.627 for UISA participants in the final model, suggesting that time to failure is 37.3 per cent lower than before the introduction of UISA.

The results of the competing-risk analysis using the final model are summarized as follows: in the Cox model the hazard of leaving employment increases by 45.5 per cent if the following event is another employment relation, by 90.6 per cent if workers become unemployed, and by 65.5 per cent if workers become inactive. For the stratified Cox models the hazard rates increase by 42.6, 75.6, and 83.1 per cent, respectively. The parametric generalized gamma regressions return qualitatively comparable results, where time is accelerated for all following events if workers are UISA participants. The time ratios are

0.705, 0.563, and 0.535, respectively, suggesting that time to failure is 29.5 per cent lower for employment and approximately 45 per cent lower for unemployment or inactivity as the next event, compared to workers with the same next event not participating in the scheme.

Taking reduced employment duration as an indicator for higher labour market flexibility, these results suggest that the policy led to its desired outcome of tackling previously more rigid labour markets. UISA can therefore present an alternative for emerging economies that seek to improve rigidities and to allow for a more dynamic labour market, while avoiding some problems related to unemployment insurance (e.g. moral hazard). Further research may focus on a more detailed examination of the UISA design, for example on the effect of specific scheme requirements after which workers become eligible to withdraw accumulated benefits.

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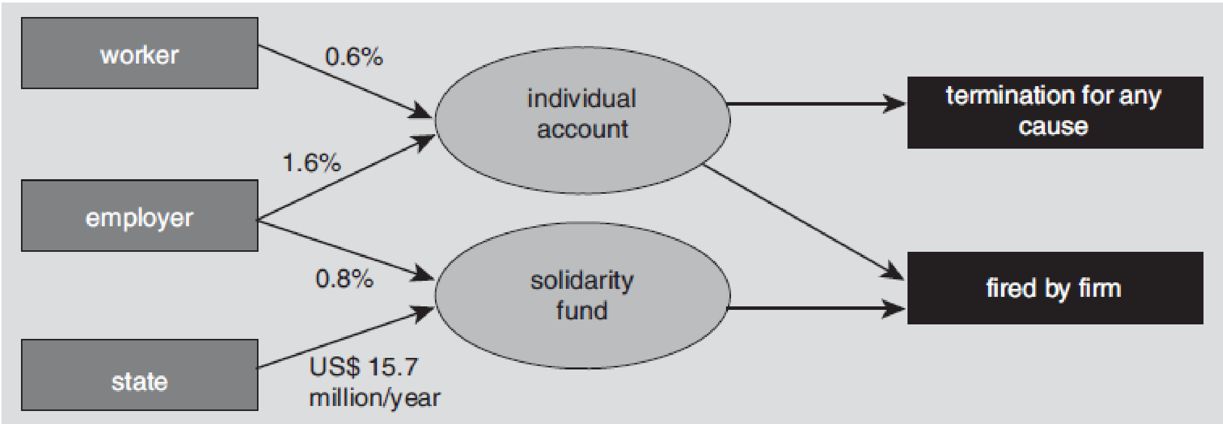
A Appendix: Overview UISA Scheme

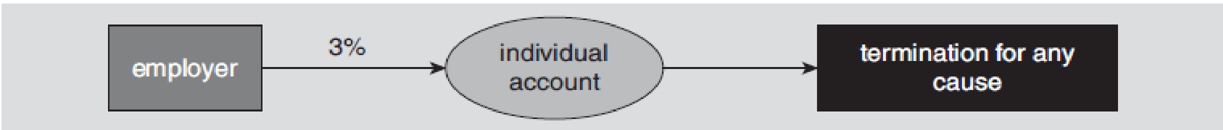
Contribution scheme to individual savings accounts and the solidarity fund:

Figure 6 - Workers with open-ended contracts



Source: Berstein, Fajnzylber and Gana (2012).

Figure 7 - Workers with temporary contracts



Source: Berstein, Fajnzylber and Gana (2012).

B Appendix: Descriptive Statistics

Table 7 - Summary statistics

VARIABLE	Obs	Mean	Std. Dev.	Min	Max
Dummy Variables					
Temporary Contract	2,323	0.50	0.50	0	1
Female	2,323	0.38	0.48	0	1
Knowledge of UISA	2,323	0.22	0.42	0	1
Metropolitan Region	2,323	0.36	0.48	0	1
UISA	2,323	0.36	0.48	0	1
Married	2,210	0.56	0.50	0	1
Categorical Variables					
Education Categories	2,319	1.90	0.83	1	4
Income Categories	2,032	3.09	0.83	1	5
Next Event	1,980	1.76	0.71	1	3
Continuous Variables					
Age	2,323	33.15	11.39	18	74
Children	2,323	0.89	0.74	0	8
Employment Duration	2,323	28.64	29.26	1	95
Firm Size	2,294	18.76	282.75	1	12,000
Hours	2,296	48.48	8.47	2	84
Household Size	2,323	4.77	2.09	1	24
Risk Aversion	2,293	5.48	3.18	0	10
Working Household Members	2,323	0.98	0.97	0	7

Data manipulation: 16 hours observations changed to missing, as workers reported to work over 84 hours per week.

C Appendix: Test of Proportional Hazards Assumption

Multiple Cox regression

Table 8 - Test of proportional hazards assumption

Time: Log(t)

VARIABLE	Base Specification	Final Model	Interactions
		Schoenfeld Residuals	
UISA	0.819	0.001	0.978
Female	0.039	0.081	0.149
Age	0.034	0.036	0.022
Temp. Contract	0.000	0.000	0.000
Education			
- High School	0.556	0. 759	0.630
- Prof. Formation	0.833	0.956	0.476
- Univ. and higher	0.701	0.159	0.058
Hours		0.069	0.108
Income			
- 100,000 CLP		0.017	0.002
- 200,000 CLP		0.002	0.000
- 300,000 CLP		0.000	0.000
> 300,000 CLP		0.001	0.000
Household Size		0.188	0.278
UISA x Temp. Contract			0.413
UISA x High School			0.370
UISA x Prof. Formation			0.970
UISA x Univ. and higher			0.584
Global Test	0.000	0.000	0.000

Competing-risk

Table 9 - Test of proportional hazards assumption

VARIABLE	T_1 - Employment	T_2 - Unemployment	T_3 - Inactivity
	Schoenfeld Residuals		
UISA	0.694	0.018	0.016
Female	0.087	0.031	0.238
Age	0.581	0.309	0.000
Temp. Contract	0.000	0.000	0.005
Education			
- High School	0.117	0.446	0.101
- Prof. Formation	0.089	0.315	0.355
- Univ. and higher	0.237	0.472	0.000
Hours	0.199	0.158	0.474
Income			
- 100,000 CLP	0.182	0.753	0.594
- 200,000 CLP	0.032	0.876	0.458
- 300,000 CLP	0.024	0.616	0.332
> 300,000 CLP	0.040	0.870	0.095
Household Size	0.327	0.186	0.123
Global Test	0.000	0.000	0.000

Notes: the PH test is performed on the final model.

D Appendix: Stratified Cox Model

Table 10 - Stratified Cox model

VARIABLE	Base Specification	Final Model	Interactions
		Coefficients	
UISA	0.255***	0.541***	0.589***
- UISA marg. effect			0.518***
Female	0.265***	0.2160**	0.196***
Age	-0.005***	-	-
Temp. Contract	-	-	-
Education			
- High School	-0.180***	-0.144**	-0.037
- Prof. Formation	-0.227**	0.013	0.120
- Univ. and higher	-0.442***	-0.151	-0.001
Hours		-	0.012
Income			
- 100,000 CLP		-0. 017	-0.020
- 200,000 CLP		-0.274	-0.284
- 300,000 CLP		-0.540**	-0.539**
> 300,000 CLP		-0.561**	-0.582**
Household Size		-0.016	-0.014
UISA x Temp. Contract			0.246*
UISA x High School			-0.260**
UISA x Prof. Formation			-0.262
UISA x Univ. and higher			-0.385
Strata			
Age	-	YES	YES
Contract Type	YES	YES	YES
Hours	-	YES	YES
Global PH Test	0.1822	0.8125	0.7166
Log Likelihood	-12,546	-2,417	-2,413
AIC	25,103	4,854	4,854
Pseudo R2	0.003	0.020	0.021
Wald Test Education	0.000	0.107	0.059
Wald Test Income		0.000	0.000
Employment Exit	1,976	1,691	1,691
At Risk	66,484	63,986	63,986
N	2,319	2,028	2,028

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

Competing-risk

Table 11 - Stratified Cox model

VARIABLES	T_1 - Employment	T_2 - Unemployment	T_3 - Inactivity
		Coefficients	
UISA	0.355***	0.563***	0.605***
Female	-0.345***	0.368***	1.251***
Age	-	-	-
Temp. Contract	-	-	-
Education			
- High School	0.113	-0.230**	-0.426**
- Prof. Formation	0.277*	-0.472**	0.238
- Univ. and higher	0.128	-0.740***	0.338
Hours	-0.002	0.017***	0.007
Income			
- 100,000 CLP	-0.591**	0.484	0.773
- 200,000 CLP	-0.784***	0.198	0.143
- 300,000 CLP	-0.979***	-0.114	-0.553
> 300,000 CLP	-0.915***	-0.429	-0.769
Household Size	0.000	-0.015	-0.055
Strata			
Age	YES	YES	YES
Temp. Contract	YES	YES	YES
Global PH Test	0.4307	0.2553	0.4192
Log Likelihood	-1,941	-1,745	-553
AIC	3,904	3,512	1,128
Pseudo R2	0.011	0.035	0.110
Wald Test Education	0.319	0.001	0.002
Wald Test Income	0.002	0.000	0.000
Employment Exit	741	689	240
At Risk	63,427	63,427	63,427
N	2,006	2,006	2,006

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. adjusted clustered by ID)

E Appendix: Extended Sample

The extended sample includes workers starting two years before and two years after the introduction of UISA, in contrast to the sample of the previous analysis that included workers starting one year before and one year after the introduction of UISA. 2,473 workers started their employment in the two years before and 1,814 workers in the two years after the introduction, containing 2,770 individuals.

Using the extended sample regressions (1) to (4) replicate the analysis of 6.2 (semi-parametric Cox model) in table 12, including the simple model, the base specification, the final regression and the regression with interactions. Results are qualitatively comparable with the one-year analysis: UISA participation is statistically significant at a 1 per cent level throughout the regressions, and increases the hazard of leaving employment. Quantitatively hazard rates are lower compared to the one-year sample, the differences are however not large: in the final model, for example, the one-year analysis returns an elevated hazard of 67.7 per cent, while in the two-year analysis the hazard is increased by 54.2 per cent.

Regressions (5) to (8) additionally include year dummies for workers starting one or two years before the introduction of UISA, and one or two years after the introduction. Year dummies for year one or two after UISA introduction are not statistically different from each other and are combined in the UISA variable. The dummy variable "Year Dummy" in the regression output contains workers who started two years before the UISA introduction, with the reference category referring to all workers who started in the year before. Interpreting the regression results, workers who started a new employment two years before the UISA introduction return an elevated hazard rate compared to workers starting a new employment in the year before. UISA participants of year one and two equally return an elevated hazard rate compared to the reference category.

Table 12 - Regression table Cox model

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Coefficients				
UISA	0.202***	0.163***	0.433***	0.470***	0.247***	0.247***	0.473***	0.513***
- UISA marg. effect				0.413***				0.446***
Year Dummy					0.114***	0.225***	0.122**	0.096*
Female		0.279***	0.197***	0.176***		0.278***	0.199***	0.185***
Age		-0.007***	-0.006***	-0.007***		-0.007***	-0.006***	-0.007***
Temp. Contract		1.050***	0.976***	0.830***		1.064***	0.985***	0.848***
Education								
- High School		-0.157***	-0.102**	0.039		-0.150***	-0.099*	0.045
- Prof. Formation		-0.244***	-0.117	0.033		-0.251***	-0.125*	0.024
- Univ. and higher		-0.346***	-0.109	0.041		-0.341***	-0.111	0.034
Hours			0.011***	0.011***			0.011***	0.011***
Income								
- 100,000 CLP			-0.127	-0.153			-0.127	-0.155
- 200,000 CLP			-0.365**	-0.403**			-0.362**	-0.400**
- 300,000 CLP			-0.523***	-0.562***			-0.520***	-0.555***
> 300,000 CLP			-0.629***	-0.661***			-0.620***	-0.647
Household Size			-0.018*	-0.017			-0.017*	-0.019*
UISA x Temp. Contract				0.295***				0.272***
UISA x High School				-0.271***				-0.284***
UISA x Prof. Formation				-0.318**				-0.213**
UISA x Univ. and higher				-0.297*				-0.315*
Log Likelihood	-28,093	-27,514	-22,047	-22,029	-28,090	-27,501	-22,045	-22,310
AIC	56, 188	55,041	44,120	44,092	56,183	55,019	44,117	44,657
Pseudo R2	0.001	0.019	0.022	0.023	0.001	0.020	0.022	0.023
Wald Test Education		0.000	0.213	0.048		0.000	0.216	0.030
Wald Test Income			0.000	0.000			0.000	0.000
Exit	3,654	3,648	2,989	2,989	3,654	3,648	2,989	2,989
At Risk	116,606	116,538	109,905	109,905	116,606	116,538	109,905	109,905
N	4,287	4,281	3,606	3,606	4,287	4,281	3,606	3,606

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

Notes: The year dummy includes all workers who started employment two years before the UISA introduction. The year dummies for year one and two after the policy introduction are not statistically different from each other and are combined in the UISA variable. The reference group are all workers who started a new employment in the year before UISA were introduced.

F Appendix: Control Group - Public Sector Employees

As control group I take a sample of public sector employees and equally separate them by the starting date of their employment, as previously done for the formal private sector employees. Public sector employees were not affected by the policy introduction and can serve as a control group for this analysis. Taking informal workers in the private sector, however, could return misleading results: the policy introduction could lead to a change in the behaviour of informal workers, as formal employment becomes more attractive after the introduction of UISA. For employers the cost of hiring decreases and could possibly increase the number of formal labour relations.

In regression table 13 I use the variable UISA to indicate if the public sector employees started their employment before or after October 2002. 107 employment relations were started before October 2002, 78 after that date, containing overall 172 individuals. Regressions (1) to (4) replicate the analysis of 6.2 (semi-parametric Cox model) including the simple model, the base specification, the final regression and the regression with interactions. In all regressions the UISA variable is not statistically significant, resulting in no significant difference in employment duration between both groups. Regressions (5) to (7) replicate the parametric models of section 6.3, using again the generalized gamma distribution, as the AIC returned the lowest value for this shape. I take the same regressions as before, except of the interaction model: due to the relatively low number of observations, a discontinuous region was encountered and the regression could not be computed. In the parametric models, the UISA variable is equally not significant, resulting in no significant difference in employment duration between both groups.

Table 13 - Regression table Cox model

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Coefficients				*Acceleration Parameters*	
UISA	0.126	0.109	0.274	-0.438	-0.151	-0.066	-0.347
- UISA marg. effect				0.150			
Female		0.150	0.172	0.156		-0.219	-0.109
Age		-0.015*	-0.015	-0.022**		0.022**	0.025**
Temp. Contract		1.368***	1.150***	0.682**		-1.795***	-1.489***
Education							
- High School		-0.307	-0.545*	-0.739*		0.621**	0.785**
- Prof. Formation		-0.678*	-0.959**	-0.439		0.909**	1.012**
- Univ. and higher		0.108	-0.009	0.117		0.335	0.534
Hours			-0.012	-0.014			0.021*
Income							
- 100,000 CLP			-0.130	-0.342			-0.019
- 200,000 CLP			-0.005	-0.281			-0.080
- 300,000 CLP			-0.341	-0.766			0.185
> 300,000 CLP			-0.496	-0.861			0.359
Household Size			-0.136**	-0.140**			0.178***
UISA x Temp. Contract				1.207***			
UISA x High School				0.489			
UISA x Prof. Formation				-1.238			
UISA x Univ. and higher				-0.151			
_const					2.072***	2.642***	0.631
/ln_sig					0.457***	0.357***	0.322***
/kappa					-1.568***	-0.668**	-0.718**
sigma					1.579	1.429	1.381
Log Likelihood	-624	-592	-521	-514	-308	-275	-245
AIC	1,250	1,199	1,067	1,062	625	571	521
Pseudo R2	0.000	0.051	0.058	0.071			
Wald Test Education		0.044	0.053	0.114		0.055	0.060
Wald Test Income			0.794	0.386			0.882
Exit	132	132	119	119	132	132	119
At Risk	6,887	6,887	6,506	6,506	6,887	6,887	6,506
N	185	185	169	169	185	185	169

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

1 Introduction

The introduction of unemployment insurance savings accounts (UISA) in October 2002 changed labour market conditions for formal private sector workers in Chile. Before the introduction, unemployment protection was limited to severance pay in case of job termination due to economic necessities of the firm. Additionally, high opportunity costs were involved in job change, and employers had to deal with rigid labour market regulations. After the introduction of UISA, the amount of benefits transferred to workers in case of unemployment or inactivity increased, and opportunity costs of workers changing employment decreased, while ad hoc obligations of employers to lay off workforce were reduced.

While incentives to leave unemployment have been studied in this context (Reyes, van Ours, & Vodopivec, 2010), this study is the first to empirically investigate the effect of UISA on employment duration. In this paper I fill the gap by using longitudinal social protection data containing information of employment duration of formal private sector workers before and after the introduction of the policy. The paper examines (i) whether the introduction of UISA affected employment duration among formal private sector workers, and (ii) the magnitude of this effect. Following the policy introduction, I expect that workers reacted to the changes by reduced employment duration.

I conduct an empirical analysis using survival analysis techniques to analyse employment duration: in the first part of the analysis I focus exclusively on the failure of the employment relation: if the current employment relation was terminated, irrespective of the event that follows. In the second part I apply a competing-risk model, where the different following events after employment termination are taken into account.

The results confirm that workers participating in the scheme show an increased hazard ratio of leaving employment, or accelerated time to employment termination, suggesting shorter employment duration and higher mobility of the workforce: they have a higher hazard of leaving employment in the Cox model, or accelerated time to failure in the parametric analysis, with this effect being statistically significant throughout the analysis. In the competing-risk analysis, the outcome is equally significant if the following event is another employment relation or unemployment, and for the final regression model in the case of inactivity. The effect is larger for workers becoming unemployed or inactive compared to workers changing jobs.

The paper is organized as follows: After the introduction, section 2 describes the Chilean UISA scheme, followed by a literature review on severance pay and labour mobility in section 3. Section 4 specifies the database used for the analysis, including descriptive statistics of relevant variables. Section 5 describes the method used for the analysis. In section 6 I apply survival analysis techniques for the empirical analysis: I start with non-parametric analysis using the Kaplan-Meier estimator, continue with the semi-

parametric Cox model and parametric models, before finalizing the analysis with competing-risk models where three different possible endpoints are taken into account. The final section concludes.

2 The Chilean UISA Scheme - What has Changed?

Before the introduction of UISA, severance pay[1] was the principal form of unemployment protection in Chile for workers dismissed due to Labour Code 161,[2] complemented by benefits financed by Social Security. This implied restricted financial support during unemployment spells, as only workers who lost their employment before the expiration of the contractual agreement due to economic or other needs of the firm received benefits, without guarantee of payout of the severance liabilities, as firms tried to evade the payment or were financially unable to transfer the amount. The complementary benefits by the Social Security were minimal and independent of previous salaries.[3] Severance pay also led to inflexible labour markets, making it difficult for firms to adjust their workforce in times of economic constraints, or during a firm crisis due to high payment obligations. In addition, workers lost their accumulated rights to severance pay in case of job change leading to high opportunity costs. In October 2002 the new unemployment policy was implemented as a reaction to the previous unsatisfactory situation of formal private sector workers (Acevedo, Eskenasi, & Pagés, 2006).

Unemployment protection changed from Social Security into individual savings accounts backed up by a solidarity fund (SF). For employees with a permanent contract contributions are financed by both workers and employers, and are split between the individual accounts to save up for possible unemployment spells and the SF. The latter is also co-financed by the government (Reyes, van Ours, & Vodopivec, 2010) and presents the insurance part of the scheme. For employees with a temporary contract only the employer contributes to the savings account and workers do not have access to the SF.[4, 5]

Transfers were considerably extended in terms of eligibility and total amount transferred. The transfer of benefits was extended to workers terminating their employment for just cause,[6] conditional that they worked for a pre-defined amount of time: six months for workers with temporary contracts and twelve months for workers with open-ended contracts, continuous or discontinuous. Workers receive access to their individual savings accounts when terminating employment, and are better protected compared to the

[1] For each completed year of employment, workers are entitled to one month severance pay with a maximum of eleven years.
[2] Article 161 of the labor code: dismissal due to company needs (economic reason or downsizing).
[3] Benefits were indexed to the minimum wage to reflect purchasing power; the observed minimum wage growth was however always below the average wage growth within the economy. This resulted in decreasing replacement rates over time: from 14.8 percent in 1985 to 6.3 percent in 1995 to 4.4 percent in 2001. Replacement rates increased to over 30 percent after UISA introduction compared to Social Security benefits (Ferrada, 2010).
[4] Since a reform in May 2009 workers with temporary contracts are also eligible to receive unemployment benefits through the solidarity pillar.
[5] Appendix A includes two figures with an overview of the Chilean UISA scheme.
[6] Just causes include: expiration of contract, voluntary resignation, or misconduct.

previous state. Workers with open-ended contracts losing their job due to Labour Code 161 are equally better protected, as they have, apart from their accumulated savings, access to the solidarity fund in case of low individual savings and therefore access to the insurance component of the scheme. Although the previously existing unemployment subsidy lasting for twelve months was replaced by the savings accounts with transfers lasting for a maximum of five months, the current support system is more generous, translating into overall higher transfers. Finally, workers who do not become unemployed during their working life receive their accumulated account balance when retiring (Sehnbruch, 2004). Since the labour reform of October 2002, severance pay continues to be paid out in case of dismissal for unjust cause, with the possibility of deducting accumulated savings from the severance liabilities, improving the situation of employers.

Table 1 - Benefit changes before and after UISA introduction

EVENT	Before UISA	After UISA
Job change	Loss of accumulated rights to severance pay	Loss of severance pay (as before), keeps accumulated savings
Unemployment	Severance pay if job loss occurred due to Labour Code 161 All other cases: nothing	Severance pay (as before), transfer of accumulated savings (maximum five months), solidarity fund if applicable
Inactivity	Nothing	Transfer of accumulated savings (maximum five months)
Retirement	Nothing	Transfer of accumulated savings given account balance is positive
Death	Nothing	Transfer of remaining savings given account balance is positive to surviving dependents

Source: by author based on Acevedo, Eskenasi, & Pagés (2006).

3 Severance Pay and Labour Mobility - What do We Know?

Severance pay is a widespread form of unemployment protection, particularly in developing countries (Vodopivec M. , 2004; 2009) due to large informal labour markets and limited administrative capacities to introduce unemployment insurance (Holzman, Pouget, Vodopivec, & Weber, 2011). Severance pay is however often criticized and considered an inappropriate option for income protection. While severance pay intends to provide compensation for job loss, and to stabilize the economy by discouraging layoffs and encouraging long-term work relations, it often provides workers with limited protection during unemployment spells and distorts the behaviour of workers and firms (Feldstein & Altman, 2007; Hopenhayn & Hatchondo, 2012). High unemployment protection can have negative effects on both worker separation and accession, and consequently on labour turnover and mobility.[7] Severance pay increases firing costs and reduces consequently the probability that workers become unemployed, but also hinders job creation (Blanchard, 2000) and decreases the dynamics of structural change due to reduced mobility of the workforce (Calmfors & Holmlund, 2000). A number of studies additionally confirm the link between higher job security and lower employment levels.[8] In the case of Chile the existence of severance pay resulted in higher formal employment and increased protection rights for older and high-skilled workers, while it reduced labour market opportunities for younger and unskilled workers in the period from 1960 to 1998 (Montenegro & Pagés, 2004).[9]

Empirical papers on the effects of UISA on the transition from severance pay to UISA, and particularly on changes in workers' behaviour are still rare and many researchers have relied on simulations instead.[10] One empirical paper by Kugler (2002) documents the transition from severance pay to UISA in Colombia in 1990. Results show that although UISA partly substitute employer insurance with self-insurance in form of lower wages, the scheme smoothes consumption for the unemployed. The introduction of UISA also reduces distortions in the labour market by increasing both hiring and dismissals, and leads to higher labour mobility. In the case of Chile, a number of papers have analysed the transition in a more general context: Acevedo, Eskenasi, & Pagés (2006) discuss the political, social, and economic situation in which this programme was implemented and assess the challenges. Sehnbruch (2004) concentrates on embedding the new Chilean unemployment scheme into the context of Latin American labour market legislation, while Sehnbruch (2006) examines how the scheme works in practice and whether it can serve as a model for other emerging and developing economics. Berstein, Fajnzylber, & Gana (2012) analyse the Chilean UISA scheme as a whole and provide an overview of outcomes and reforms since its implementation.

The effect of UISA on employment duration (and consequently on labour mobility) for Chile is hitherto unclear and provides little evidence: while Berstein, Contreras & Benvin (2008) show that formal private sector workers value the new unemployment benefits more than its cost,[11] limited knowledge about UISA and its design could however work against a change in labour mobility (Poblete, 2011). A first study by Reyes (2005) on duration of employment contracts using life tables suggests that workers participating in UISA show shorter employment duration with 33 per cent "surviving" the first year of employment,

[7] Cross-country evidence, among others: Boeri & Garibaldi (2009), Gomez-Salvador, Messina, & Vallanti (2004), Messina & Vallanti (2007).
[8] Among others: Haffner et al. (2001), Heckman & Pagés (2000), Haltiwanger, Scarpetta and Vodopivec (2003).
[9] For a more extensive literature overview on severance pay, see also Holzman et al. (2011).
[10] Among others: Feldstein & Altman (2007), Fölster (1999; 2001), Vodopivec (2010).
[11] They value the benefits to different extent, depending on risk aversion, gender and educational level, but always equal or more than its costs. The authors conduct an evaluation of worker's lifetime utility with and without UISA: lifetime consumption preferences of individuals are described with a constant absolute risk aversion (CARA), allowing them to smooth consumption while economically active.

compared to 52 per cent for workers not participating. The author then focuses on workers below the age of 30 to reduce selection bias and finds that workers participating in UISA still show a difference of 7 percentage points compared to workers not participating. In his paper the author uses a different database[12] and concentrates specifically on methodological issues to assess this question.

4 Database and Descriptive Statistics

The panel database used for this analysis is the Chilean EPS database,[13] a longitudinal survey with questions on the individual and household level about the Chilean labour market and social protection system. The survey was conducted in 2002, 2004, 2006 and 2009 and contains retrospective data since January 1980. The data can be matched by a unique identifier to create a panel.[14]

The database is described as follows: The first round was conducted in 2002, and was drawn from a frame of 8.1 million current and former members of the Chilean pension system included for at least one month in the timeframe 1980-2001 containing 17,246 individuals, 937 of them reported by surviving relatives. The survey was extended in 2004 with non-participating individuals, completing the base sample, and has been since then representative on the national and regional level for the entire Chilean population. Since 2004 the data is linked to the administrative records of the pension scheme, health insurance, Chile Solidario and other welfare programmes. In 2004 new health and wealth questions were added to the questionnaire. In 2006 and 2009 the sample was kept, and includes approximately 16,000 individuals (15 years and older) of all regions.[15]

The EPS is the first panel survey conducted in Chile with four rounds of data collection covering this range of thematic areas. The questionnaires remain approximately stable over the survey rounds, containing questions on labour history and provisional systems, additional information on education, health, social protection, labour training, property and patrimony, family history and housing. This survey format allows studying the impact of different governmental programmes which have been implemented over the past three decades.

For the analysis I focus on specific variables of the EPS database: the dependent variable is length of employment duration for private sector workers measured in months, the main independent variable participation in the UISA scheme. Further explanatory variables included are *general information of the worker*: gender, age, education, risk aversion, household size, working household members, civil status,

[12] Database used: Administrative records of the contribution history and benefits paid to the workers participating in the unemployment benefit programme by the Superintendencia de Pensiones.
[13] Encuesta de Protección Social in Spanish, or social protection survey.
[14] The survey is conducted by the Centre for Microdata, Department of Economics, of the University of Chile (Centro Microdatos, Universidad de Chile) with the support of the University of Pennsylvania.
[15] In each survey round three different types of questionnaires account for repeated, new and deceased participants.

children, and *work related information of the worker*: contract type, hours worked per week, monthly net income, firm size, region of employment, and knowledge of UISA.[16]

The database for the analysis consists of 2,323 employment relations of dependent private sector employees: 1,489 employment relations started in the year before the policy introduction, between October 2001 and September 2002, and workers do not participate in the UISA scheme. 834 employment relations started in the year after the policy introduction, between October 2002 and September 2003, and workers compulsorily joined the new unemployment scheme. Although the complete database consists of approximately 16,000 individuals, I selected formal private sectors workers of 18 years and older who started employment in the year before and after UISA introduction into the sample for this analysis, leading to a reduced database of 2,323 employment relations, and 1,848 individuals.

Table 2 reports longer employment duration for workers not participating in the UISA scheme. This result can be however misleading, as these workers started employment in the year before the workers participating in the scheme. Additionally, 343 observations are censored, therefore still ongoing at the moment of the last survey round, leading to an expected downward bias of the estimated mean. Some individuals were also observed more than once, if they ended their employment within the considered time frame and started a new employment, and cannot be considered independent observations.[17]

Table 2 - Average employment duration

UISA	Months	St. Err.	[95% Conf. Interval]		Freq.
Before	31.9	0.80	30.37	33.50	1,489
After	22.8	0.87	21.04	24.47	834
Total	28.6				2,323

For the competing-risk analysis, I additionally take the following event into account, after finishing the initial employment relation. For workers who ended their employment within the survey rounds, the distribution of the following event is divided into: 798 individuals changed into a new employment, 864 became unemployed, and 318 became inactive. The following event is approximately equally distributed between change in employment, and unemployment with ca. 40 per cent for each event. Slightly more

[16] Summary statistics of all variables in appendix B.

[17] Repeated spells: throughout the analysis I run the regressions by clustering the observations by their unique identifier. By specifying clusters the single observations are not considered independent, but the clusters defined. Due to repeated spells in the data set, I clustered the ID of the observations, as the same worker can be observed more than once since more than one job can be started during the two year period considered. It is reasonable to assume independence of individuals, but not within different observations of the same individual. The data set contains 2,323 observations and 1,848 individuals. Specifying the ID clusters in the regressions, I obtain robust standard errors. In case of observing intra-cluster correlations, the robust standard errors are better indicators for estimator variability, resulting in more accurate outcomes.
Models with individual-level frailties (random-effect models in survival analysis) did not converge.

workers face unemployment after terminating their current employment relation, compared to a new employment contract. Inactivity is observed among 16 per cent of the workers.

5 Method - Survival Analysis

I conduct the analysis using survival analysis techniques, also known as event history or duration analysis. It is defined as the analysis of time until the occurrence of a specific event, from a pre-defined starting point to the transition from one state to another, conditional that it has not yet occurred. In this analysis the time of interest is represented by the duration in one specific employment relation, the event of interest represented by terminating this employment period. Workers are throughout time 'at risk' of terminating employment and experiencing the failure event (Box-Steffensmeier & Jones, 2004).

Survival analysis is different from Ordinary Least Square (OLS) regressions for a number of reasons and requires a special framework: first, the normality distribution of residuals cannot be assumed, as normality of time is unreasonable for many events. The risk of the event occurring is generally not constant over time and almost certainly non-symmetric (e.g. bi-modal). Second duration, or time to failure, is always positive. And third it encounters the problem of right censoring: the observed individual participates in the survey, but the event might not have yet occurred when the survey finishes. In this case the policy was introduced in October 2002, and the last survey round available records data until early 2010. The workers remaining in their current employment are no longer observed until the following survey round is conducted and published, and are censored. In the analysis I assume non-informative censoring meaning that the censoring time of an individual tells nothing about the risk after that time.

There are three main approaches in survival analysis: non-parametric analysis, the semi-parametric Cox proportional hazards (PH) model and parametric models. While non-parametric and semi-parametric models compare subjects at the time when failures actually occur, parametric models use probabilities that describe what occurs over the whole interval given the information of the subject during time x_j (Cleves, Gutierrez, Gould, & Marchenko, 2010). To be more specific: non-parametric analysis assumes no functional form of the survivor function and makes therefore no assumption about the hazard or cumulative hazard, so 'letting the data set speak for itself'. The effects of additional sets of covariates are not modelled either, and the comparison is performed on a qualitative level. In the semi-parametric Cox model the parametric shape is equally left unspecified, but the model assumes that covariates have proportional baseline hazards. Parametric models are either written as linear regressions, in the hazard parameterization, or in the log-time parameterization, also known as accelerated failure time (AFT) metric. All parametric models make assumptions about the shape of the hazard function, with the simplest being the exponential model assuming a constant hazard over time. Further models include Weibull or

Gompertz distributions (flat, monotonically increasing or decreasing hazard rates), log-normal and log-logistic models (non-monotonic hazard rates) and the flexible three-parameter generalized gamma distribution (Cleves, Gutierrez, Gould, & Marchenko, 2010).

Estimates are obtained by calculating the maximum likelihood for parametric, and by calculating the partial likelihood for semi-parametric models. Breslow or Efron approximations are used to compute the partial likelihood in case failure events are tied in the data set. The maximum likelihood function assuming non-informative censoring includes censored observations with survival time t_i and failure indicator d_i (taking the value 1 for failures and 0 for censored observations) and has the form

$$L = \prod_{i=1}^{n} S(t_i|x_i, \beta)\ \lambda\left(t_i\middle|x_{i,\beta}\right)^{d_i} \tag{1}$$

and the partial likelihood with k distinct observed failure times and no ties

$$L = \prod_{j=1}^{k} \left\{\frac{\exp\,(x_j\beta_x)}{\sum_{i\epsilon R_j} \exp\,(x_j\beta_x)}\right\} \tag{2}$$

(Cleves, Gutierrez, Gould, & Marchenko, 2010) and (Rodríguez, 2010).

In a first step, I estimate the survivor function without assuming any particular functional form. The Kaplan-Meier estimator, a non-parametric estimator of the survivor function S(t), estimates the probability of survival past a certain time t and is given by

$$\hat{S}(\mathrm{t}) = \prod_{j|t_j \leq t} \frac{n_j - d_j}{n_j} \tag{3}$$

where n_j represents the number of individuals at risk at time t_j and d_j represents the number of failures at time t_j. This stepwise function shows the survival of workers in their employment, presenting first results of survival between workers who are participating in the UISA scheme compared to those who are not.

In a second step, I analyse the survival of employment using the semi-parametric Cox model. The Cox proportional hazards model (Cox, 1972) and (Cox, 1975) is given by

$$\lambda\ (\mathrm{t}|x_j) = \lambda_0(\mathrm{t})\ \exp(x_j\beta_x) \tag{4}$$

where λ_0(t) is the baseline hazard and $x_j\beta_x$ the covariates and regression parameters. The baseline hazard is not given a particular parametrization and is left unestimated. The model makes no assumption about the hazard shape over time, but all individuals are assumed to have the same hazard over time, meaning that the hazard rate for any two individuals at any point in time is proportional (Cleves, Gutierrez, Gould, & Marchenko, 2010).

In a third step, I select a functional form for the hazard rate using the Akaike Information Criterion (AIC) and parameterize the shape of the hazard function. Parametric estimations use probabilities that describe the data over the whole time interval given what is known about the observations during this time.

Parametric models are written in two different ways:

in the hazard metric,

$$h(t|x_j) = h_0(\mathrm{t}) \exp(x_j \beta_x) \tag{5}$$

in the log-time metric, also known as the AFT metric,

$$\ln(t_j) = x_j \beta_x + \epsilon_j. \tag{6}$$

Hazard parameterizations can fit exponential, Weibull and Gompertz distributions. Widely used log-time parameterizations are exponential, Weibull, log-normal, log-logistic and the generalized gamma distribution (Cleves, Gutierrez, Gould, & Marchenko, 2010).

In a fourth and final step, I apply a competing-risk model to the data, where the endpoint consists of several distinct events and the failure can be attributed to one event exclusively to the others. In a competing risk model I am interested in the cause-specific hazard function:

$$\lambda_j\ (\mathrm{t}) = \lim_{\Delta \to 0+} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t} \tag{7}$$

where λ_j indicates the hazard rate for a single-state process where the hazard rate is subscripted for each of the j events that can occur. To conduct the analysis I censor all events, but the event of interest. Each part of the product can be then estimated separately and I obtain risk-specific hazard rates. As before, I can equally conduct non-parametric, semi-parametric and parametric analysis.

6 Empirical Analysis

The main results of the empirical analysis can be summarized as follows: in the first part of the analysis I focus exclusively on the failure event of terminating the current employment. UISA participation is significant and increases the hazard of leaving employment, or accelerates time to failure, throughout all regressions irrespective of the method selected or the covariates included in the regressions. In the second part of the analysis, results are qualitatively comparable if the following event is a new employment relation or unemployment: UISA participation is significant throughout all regressions. This is however not the case for workers becoming inactive after terminating their current employment: the difference between both groups is not significant for the Kaplan-Meier estimator, the simple regression or the base specification. Only in the final model UISA participation becomes significant. Quantitatively the effect is larger for workers becoming unemployed or inactive, compared to workers changing employment.[18]

6.1 Non-Parametric Analysis

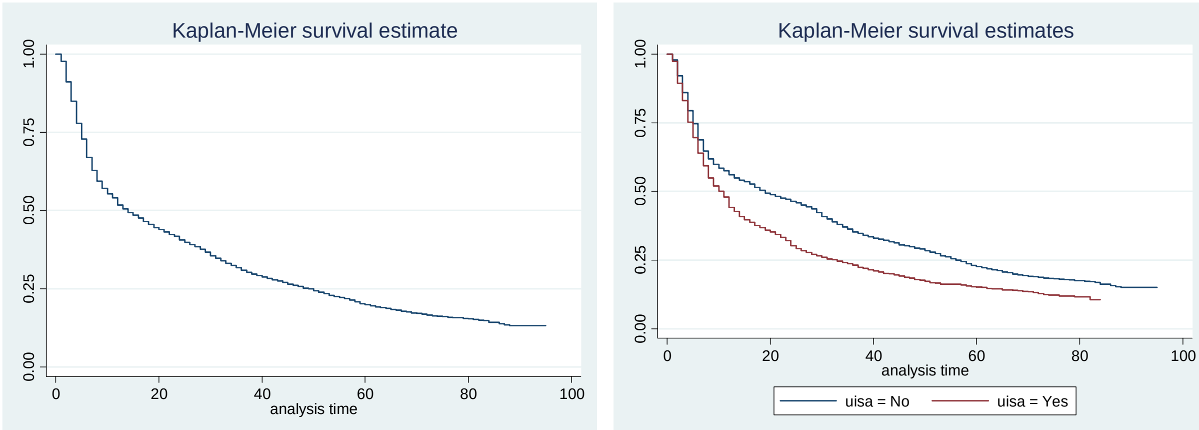
I start the empirical analysis with the Kaplan-Meier (KM) estimator: figure 1 (a) plots the overall Kaplan-Meier survival estimate, and figure 1 (b) by UISA participation. Figure 1 (a) shows a high hazard rate of employment termination during the first year of employment: after approximately twelve months, half of all workers have terminated their current employment contract. From twelve to approximately 42 months another quarter of workers terminate employment. Afterwards the number of surviving workers continues declining in a steady and moderate pace, until the final survey round finishes and approximately 15 per cent of the sample is still employed and therefore censored. In figure 1 (b) survival is similar during the first months of employment and starts diverging after approximately ten months, showing higher employment survival for workers not participating in the UISA scheme. The logrank and the Wilcoxon test confirm that the estimates are significantly different: with a p-value of 0.000 the logrank test rejects the null hypothesis that both estimates are equal and concludes that the difference in employment survival is statistically significant. Returning a p-value of 0.000, the Wilcoxon result equally rejects the null-hypothesis.[19]

[18] In addition to the continuous time analysis, I run the regressions based on discrete time analysis and use the complementary log-log regression (the discrete-time proportional hazards model) to compare if results are similar: the cloglog regressions return qualitatively comparable results, where the UISA variable is statistically significant at a 1 percent level throughout the regressions and equally increases the hazard of leaving employment. Coefficients are quantitatively above the results of continuous time analysis, the difference is however minor.

[19] With the logrank test I test the null hypothesis that the probability of employment survival of both groups is the same at any point of time. It compares the survival of both groups by taking the follow-up period into account (Bland & Altman, 2004). The Wilcoxon test is a rank test which places additional weight to earlier failure times than failures later in the distribution compared to the logrank test. In case the hazard functions are not proportional, this test is preferred over the logrank test (Cleves, Gutierrez, Gould, & Marchenko, 2010). I conduct both tests, as the proportionality assumption has not yet been tested.

Figure 1 - KM survival estimates

(a) overall **(b)** by UISA



6.2 Semi-Parametric Cox Model

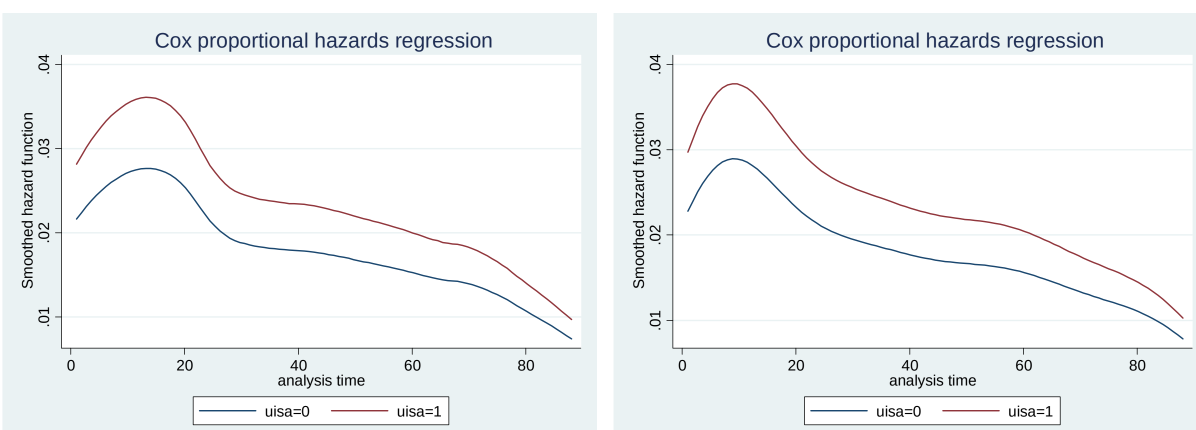
Simple Cox Regression

I continue with the simple Cox model, where I regress the main independent variable UISA on employment duration. The result in table 3 returns a coefficient of 0.273. Expressed in hazard rates the hazard of leaving employment is approximately 1.314 times higher for workers participating in the UISA scheme (hazard increases by 31.4 per cent) and is statistically significant at the 1 per cent level.

Next, I test the PH assumption of the simple Cox model. I start with a graphical analysis and plot the hazards of both groups. The hazards are estimated over the range of observed failure times, and all failure times contribute to the estimate of the baseline hazard. The hazard ratios depicted in the figures are approximately proportional:

Figure 2 - Estimated baseline hazards

(a) Epanechnikov kernel **(b)** Gaussian kernel



I also conduct a formal test based on Schoenfeld residuals. This test retrieves the residuals, fits a smooth function of time to them, and tests whether there is a relationship. For this test time is log-transformed. The result $p = 0.441$ suggests that there is no evidence of non-proportionality. I do an additional formal test by introducing an interaction between the UISA variable and time. For the test time is log-transformed and the result ($p = 0.427$) equally suggests that there is no evidence that the UISA effect changes with ln(time).

Multiple Cox Regression

I start the multiple Cox regressions by specifying a base specification. I expect the following variables to have an effect on the decision of remaining in employment: gender, age, contract type and education. Education is split into four dummy variables: basic education (the reference category), high school, professional formation and higher education (university and higher). All variables are statistically significant at the 1 per cent level, except for age significant at the 5 per cent level. The education dummies are collectively significant at the 1 per cent level. While UISA participation, female, and a temporary contract increase the hazard of leaving employment, the hazard decreases with age and a higher educational level. With a coefficient of 0.282 the effect of the UISA variable is similar to the simple regression, translating into a hazard ratio of 1.327, or a 32.7 per cent increase in the hazard of terminating employment.

Afterwards I test additional sets of covariates. First I add average net income, total hours worked per week and number of workers per firm to capture information on type, place and quality of work. Second individual risk aversion,[20] third number of household members, working household members, civil status[21] and number of children to capture information on the household composition, fourth region of work captured by a dummy variable indicating if the worker lives in the metropolitan region of Santiago, and fifth knowledge of the UISA scheme. Income is split into five dummy variables: zero income (the reference category), income up to 100,000 CLP, between 100,000 and 200,000 CLP, between 200,000 and 300,000 CLP, and above 300,000 CLP.[22] UISA participation, gender, and contract type remain statistically significant throughout all regressions, while age and education vary over the regressions. The coefficient of UISA almost doubles after including the income dummies, increasing the effect of UISA participation when income is hold constant. Throughout all regressions, income is collectively significant at the 1 per cent level. Hours worked per week is significant at the 5 per cent level, while firm size, individual risk aversion, working household members, civil status, number of children, region and

[20] Risk aversion measured by asking survey participants about their individual risk assessment on a scale from 0 (for individuals considering themselves as highly risk averse) to 10 (for individuals stating they are highly disposed to take risk).
[21] If married (includes cohabiting).
[22] On 16 July 2013: 1 Euro = 660 CLP [www.xe.com].

knowledge of UISA are not significant. Although household size is not significant in the Cox model, I decide to keep this variable as it becomes significant in other regressions. Regression (8) in table 3 presents the final Cox model, including all variables of the base specification, hours worked, average net income and household size. The UISA coefficient increases to 0.517 in the final model, translating into a hazard ratio of 1.677, or a 67.7 per cent increase in the hazard of terminating employment.

Finally, I test a number of interaction terms in regression (9).[23] The following interaction terms are significant: UISA x contract type, and UISA x education dummies. Having a temporary contract and participating in the UISA scheme additionally increases the hazard of terminating employment, above and beyond the single effects of the variables. For the other interaction term, UISA x education dummies, the hazard decreases with higher education if workers participate in the UISA scheme.[24, 25]

[23] Interactions tested:
UISA*Female, UISA*Age, UISA*Temp.Contract, UISA*Education Dummies, UISA*Income Categories, UISA*Household Size, Female*Age, Female*Temp.Contract, Age*Temp.Contract, Temp.Contract*Hours, Temp.Contract*Income Categories, Temp.Contract*Household Size.

[24] In addition to this sample, I run the regressions with an extended sample including workers who started two years before and two years after the UISA introduction. Regression results are discussed in appendix E.

[25] As control group I take a sample including public sector employees and separate the sample by workers starting in the year before and after UISA introduction in October 2002. Compared to the sample with formal private sector workers, this sample does not show statistically significant results in "UISA participation". Regression results are discussed in appendix F.

Table 3 - Regression table Cox model

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Coefficients				
UISA	0.273***	0.282***	0.513***	0.511***	0.539***	0.516***	0.517***	0.517***	0.588***
- UISA marg. effect									0.491***
Female		0.293***	0.202***	0.212***	0.219***	0.203***	0.201***	0.203***	0.171***
Age		-0.005**	-0.004*	-0.004	-0.005*	-0.005**	-0.005**	-0.005**	-0.005**
Temp. Contract		0.987***	0.916***	0.912***	0.922***	0.923***	0.912***	0.912***	0.758***
Education									
- High School		-0.207***	-0.140**	-0.149**	-0.131**	-0.147**	-0.148**	-0.150**	0.004
- Prof. Formation		-0.238***	-0.109	-0.119	-0.099	-0.105	-0.099	-0.101	0.131
- Univ. and higher		-0.444***	-0.201	-0.201	-0.153	-0.209*	-0.211*	-0.211*	-0.016
Hours			0.007**	0.007**	0.008**	0.007**	0.007**	0.007**	0.007**
Income									
- 100,000 CLP			0.073	0.066	0.062	0.084	0.066	0.067	0.085
- 200,000 CLP			-0.200	-0.196	-0.215	-0.192	-0.202	-0.201	-0.191
- 300,000 CLP			-0.433	-0.444	-0.438*	-0.444	-0.439	-0.442	-0.431
> 300,000 CLP			-0.538*	-0.547*	-0.519*	-0.541*	-0.539*	-0.543**	-0.540*
Number of Workers			0.000						
Risk Aversion				0.006					
Household Size					-0.016	-0.019	-0.019	-0.019	-0.018
Working HH Members					-0.010				
Married					-0.027				
Children					0.028				
Metropolitan Region						0.059			
Knowledge of UISA							0.028		
UISA x Temp. Contract									0.380***
UISA x High School									-0.367***
UISA x Prof. Formation									-0.536***
UISA x Univ. and higher									-0.472**
Log Likelihood	-14,022	-13,728	-11,200	-11,199	-10,691	-11,362	-11,362	-11,362	-11,345
AIC	28, 047	27,469	22,427	22,425	21,413	22,752	22,753	22,751	22,723
Pseudo R2	0.001	0.020	0.023	0.023	0.024	0.023	0.023	0.023	0.025
Wald Test Education		0.000	0.132	0.106	0.234	0.099	0.092	0.088	0.005
Wald Test Income			0.000	0.000	0.000	0.000	0.000	0.000	0.000
Exit	1,980	1,976	1,649	1,649	1,585	1,670	1,670	1,670	1,670
At Risk	66,530	66,484	62,479	62,586	59,108	63,427	63,427	63,427	63,427
N	2,323	2,319	1,982	1,981	1,899	2,006	2,006	2,006	2,006

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

Notes: Instead of hazard ratios, coefficients are reported in this table: positive coefficients increase the hazard, negative coefficients decrease the hazard. Hazard ratios are obtained by taking the exponential of the coefficient.

Next the PH assumption is tested for the base specification, the final Cox model and the Cox model with interactions. For the Cox model to be valid and to satisfy the PH assumption, the global PH test must return p-values above the threshold of 10 per cent. The global PH test reports for the three regressions p-values of 0.000,[26] rejecting the PH assumption and making the Cox model invalid. While UISA participation and education suggest that there is no evidence of non-proportionality in the base specification, gender, age and contract type report p-values below the 10 per cent threshold. In the final Cox model various variables have low p-values: UISA participation, gender, age, contract type, and the income dummies. The results are similar for the interaction model, except for UISA participation and gender, where the p-values are above the threshold value. A stratified Cox model presents a possible solution when certain covariates do not satisfy the PH assumption (Ata & Sözer, 2007).

Stratified Cox Model

Due to the previous results, I relax the assumption that every individual faces the same baseline hazard,

$$\mathrm{h}(\mathrm{t}|x_j) = h_0(\mathrm{t}) \exp(x_j \beta_x) \tag{8}$$

in favour of

$$\mathrm{h}(\mathrm{t}|x_j) = h_{01}(\mathrm{t}) \exp(x_j \beta_x), \qquad \text{if } j \text{ is in group 1} \tag{9}$$

$$\mathrm{h}(\mathrm{t}|x_j) = h_{02}(\mathrm{t}) \exp(x_j \beta_x), \qquad \text{if } j \text{ is in group 2} \tag{10}$$

The baseline hazards can now differ across the levels of stratified variables, but the coefficients β_x continue to be the same (Cleves, Gutierrez, Gould, & Marchenko, 2010). Covariates returning high p-values are assumed to satisfy the PH assumption and are included in the model, while covariates that do not fulfil this criterion and report low p-values are stratified (Ata & Sözer, 2007).

I apply the stratified model to the data: after testing different sets of stratified regressions, I stratify contract type in the base specification, and age, contract type and hours in the final model and the interaction model. The global PH tests return a p-value of 0.182 for the base specification, a p-value of 0.813 for the final model and a p-value of 0.717 for the interaction model, rejecting the evidence of non-proportionality. Using the stratified Cox model is therefore more appropriate for the data. The coefficients of UISA participation remain similar, therefore suggesting quantitatively comparable effects compared to the previous Cox regression table.[27]

[26] See table 8 in appendix C.
[27] See table 10 in appendix D.

6.3 Parametric Models

I start the parametric analysis by comparing the six parametric model shapes using the Akaike Information Criterion. The AIC penalizes each model's log likelihood to reflect the number of parameters estimated (Akaike, 1974). The preferred model distribution is the one with the lowest AIC value, in my case the generalized gamma distribution. Using this distribution, I run four regressions (simple model, base specification, final model and interaction model) and compare the results in table 4: the UISA variable is statistically significant at the 1 per cent level in all regressions, as well as age, contract type, hours worked and income. In all four regressions the UISA coefficient is negative, implying "accelerated" time to failure. Expressed as time ratios, the simple model returns a value of 0.781, suggesting that time to failure is approximately 21.9 per cent lower compared to workers not participating in the scheme. In the base specification time to failure is less accelerated for UISA participants with a time ratio of 0.850. When adding the income variables to the regressions in the final and interaction model, the UISA coefficient value decreases. The results returns a time ratio of 0.627 and 0.628 (marginal effect), respectively. Education is not significant in the final model, while income is significant at the 1 and 10 per cent level in the base specification and the interaction model, respectively. The interaction terms are significant at the 5 per cent level, and confirm the previous interpretation: participating in the UISA scheme and having a temporary contract additionally accelerate time to failure, while the interaction UISA x education decelerates time to employment termination. Analysing the parameters, the special cases of the generalized gamma distribution Weibull ($\kappa = 1$), log-normal ($\kappa = 0$) and the exponential distribution ($\kappa = \sigma = 1$) are not fulfilled.

Table 4 - Generalized gamma regressions

VARIABLE	Simple Model	Base Specification	Final Model	Interactions
	Acceleration Parameters			
UISA	-0.247***	-0.162***	-0.467***	-0.567***
- UISA marg. effect				-0.465***
Female		-0.239***	-0.179***	-0.157**
Age		0.010***	0.008***	0.009***
Temp. Contract		-1.305***	-1.203***	-1.080***
Education				
- High School		0.146**	0.068	-0.066
- Prof. Formation		0.218**	0.042	-0.125
- Univ. and higher		0.481***	0.141	-0.017
Hours			-0.011***	-0.011***
Income				
- 100,000 CLP			0.095	0.133
- 200,000 CLP			0.453**	0.493**
- 300,000 CLP			0.745***	0.772***
> 300,000 CLP			0.901***	0.934***
Household Size			0.026*	0.026*
UISA x Temp. Contract				-0.294**
UISA x High School				0.331***
UISA x Prof. Formation				0.422**
UISA x Univ. and higher				0.398
_const	2.270***	2.919***	3.258***	3.282***
/ln_sig	0.306***	0.221***	0.206***	0.199***
/kappa	-0.897***	-0.371***	-0.235***	-0.191**
sigma	1.358	1.247	1.228	1.220
Log Likelihood	-3,873	-3,575	-3,024	-3,015
AIC	7,754	7,170	6,081	6,070
Wald Test Education		0.000	0.678	0.059
Wald Test Income			0.000	0.000
Employment Exit	1,980	1,976	1,670	1,670
At Risk	66,530	66,484	63,427	63,427
N	2,323	2,319	2,006	2,006

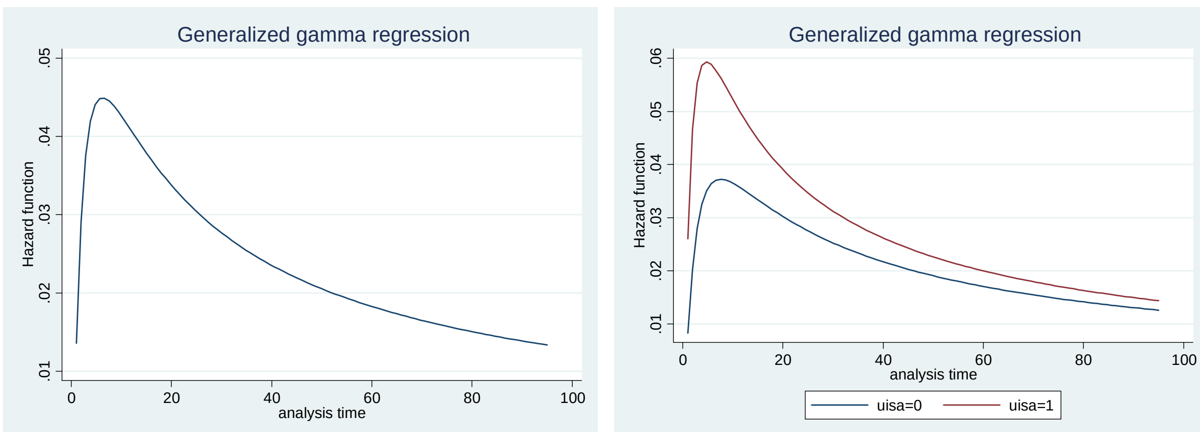
* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

Notes: The coefficients reported in table 4 are expressed as $\tau_j = \exp(-x_j \beta_x) t_j$ and are called the acceleration parameters. If coefficients are negative, they "accelerate" time, so failure is expected to occur sooner; if coefficients are positive, they "decelerate" time, so failure is expected to occur later. If coefficients are equal to zero, then time passes at its "normal" rate (Cleves, Gutierrez, Gould, & Marchenko, 2010). Another option are exponentiated coefficients, which are interpreted as time ratios.

As a last step in the parametric analysis, I run the final model, and estimate the hazard functions based on the generalized gamma distribution.[28] Figure 3 (a) returns the overall hazard, indicating a steep increase in the hazard rate during the first year of employment, with a peak after approximately 12 months, and a steady decline thereafter. Figure 3 (b) shows the hazard function by UISA participation, with a considerably higher hazard rate for UISA participants, diverging especially during the first two years of employment, and converging over the remaining time. The peak after approximately one year is more pronounced for UISA participants.

Figure 3 - Hazard functions

(a) overall **(b)** by UISA



Notes: Hazard functions are performed on the final model.

6.4 Competing-Risk Model

In a competing-risk model the failure event can occur for more than one reason. In this dataset terminating employment can lead to three different events: to another employment contract (T_1), to unemployment (T_2), or to inactivity (T_3). Only one of these three possibilities can occur at once. Compared to the previous analysis, competing-risk data focuses on the cause-specific hazard function instead of the hazard or cumulative hazard function, and on the cumulative incidence function instead of the survivor function. The cause-specific hazard function describes the risk of failure from the specific event, given the failure has not yet occurred. The cumulative incidence function (CIF) is closely related to the failure function describing the probability of failing before or up to time t, but generalizes this concept to the competing-risk model. The CIF at time t for cause j is the probability of failing from the specific cause j before or up to time t. In a competing-risk model, I can equally conduct non-parametric,

[28] I concentrate on the final model, as the AIC returns only marginally lower values for the interaction model. I additionally run the hazard functions with the interactions models, and the figures return qualitatively and quantitatively similar results.

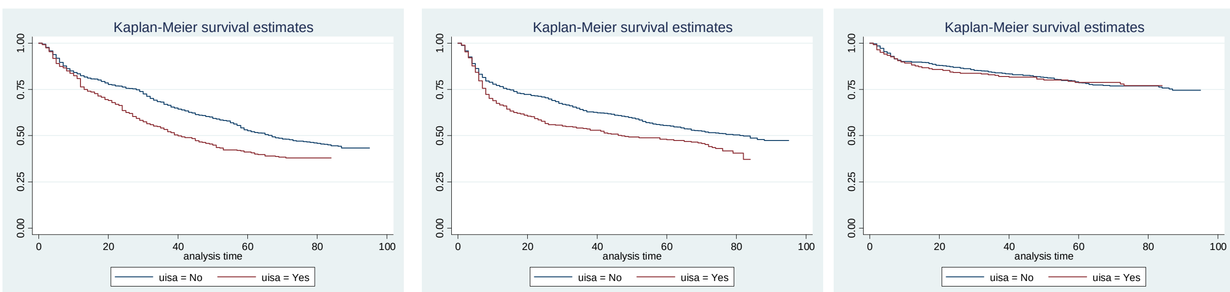
semi-parametric and parametric analysis. As before, I start with non-parametric Kaplan-Meier estimates, continue with the semi-parametric Cox model and finalize the analysis with fitting parametric models.

Non-Parametric Analysis

For figures 4 (a) and (b) the logrank and Wilcoxon test return p-values of 0.000, however not for figure 4 (c). For inactivity as the following event, the logrank test returns a p-value of 0.451, and the Wilcoxon test a p-value of 0.206, translating into no significant difference between both groups. While UISA participation makes a difference if workers change employment or become unemployed, it appears to be irrelevant for workers becoming inactive. In the first two cases the hazard ratio of UISA participants is higher compared to the workers not participating in the scheme.

Figure 4 - Kaplan-Meier survival estimates

(a) T_1 - Employment **(b)** T_2 - Unemployment **(c)** T_3 - Inactivity



Semi-Parametric Cox Model

Based on the regression table 3 of the semi-parametric analysis, I run the simple regression (1), the base specification (2) and the final model (3).[29] Different to the previous analysis, I now take into account the three different causes of employment termination. The results in table 5 vary depending on the event following employment termination. If workers change their employment, UISA participation, gender, and contract type are statistically significant variables, while age, education, hours worked, income and household size do not return significant results. If workers become unemployed all variables are significant at the 1 per cent level, except of household size. For the last option, inactivity, the picture changes over the regressions: while UISA participation does not return significant results for the simple model and the base specification, it is statistically significant at the 1 per cent level in the final model. The remaining variables are significant at the 1 or 5 per cent level, except of hours and household size.

[29] I exclude the interaction model to consolidate the competing-risk analysis.

The magnitude of the UISA effect varies according to the next event:[30] while the coefficient returns a value of 0.375, translating into a hazard ratio of 1.455 or a 45.5 per cent increase in the hazard of terminating employment when the next event is a new employment relation, the coefficient almost doubles to 0.645, translating into a hazard ratio of 1.906 or a 90.6 per cent increase in the hazard of terminating employment when the following event is unemployment. For inactivity as the next event, the coefficient returns a value of 0.504, translating into a hazard ratio of 1.655 or a 65.5 per cent increase in the hazard of terminating employment. While UISA participation has an effect on the duration of employment in all three cases and increases the hazard of terminating employment, the effect is the highest for workers becoming unemployed. The effect is also higher for inactivity compared to changing employment. A possible explanation could present the direct benefit of receiving the accumulated savings in the case of unemployment or inactivity, while a job change does not result in immediate benefits, but reduced opportunity costs.

[30] I concentrate on the coefficients of the final model.

Table 5 - Regression table Cox model

VARIABLE	T_1 - Employment			T_2 - Unemployment			T_3 - Inactivity		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	Coefficients								
UISA	0.314***	0.318***	0.375***	0.301***	0.310***	0.645***	0.090	0.050	0.504***
Female		-0.275***	-0.297***		0.363***	0.358***		1.371***	1.102***
Age		-0.004	-0.004		-0.013***	-0.013***		0.012**	0.013*
Temp. Contract		0.643***	0.642***		1.239***	1.217***		1.204***	0.849***
Education									
- High School		0.006	0.034		-0.307***	-0.276***		-0.379***	-0.294*
- Prof. Formation		0.077	0.139		-0.671***	-0.538***		0.063	0.323
- Univ. and higher		-0.069	0.003		-1.142***	-0.803***		-0.028	0.426
Hours			-0.000			0.015***			0.005
Income									
- 100,000 CLP			-0.303			0.350			0.433
- 200,00 CLP			-0.499*			0.149			-0.086
- 300,000 CLP			-0.629**			-0.099			-0.819
> 300,000 CLP			-0.576*			-0.439			-1.086
Household Size			-0.010			-0.024			-0.031
Log Likelihood	-5,556	-5,510	-5,056	-6,180	-5,940	-4,618	-2,285	-2,160	-1,588
AIC	11,114	11,033	10,139	12,363	11,895	9,261	4,572	4,334	3,201
Pseudo R2	0.002	0.010	0.012	0.001	0.035	0.045	0.000	0.055	0.056
Wald Test Education		0.859	0.804		0.000	0.000		0.013	0.008
Wald Test Income			0.112			0.005			0.000
Employment Exit	798	798	741	864	860	689	318	318	240
At Risk	66,530	66,484	63,427	66,530	66,484	63,427	66,530	66,484	63,427
N	2,323	2,319	2,006	2,323	2,319	2,006	2,323	2,319	2,006

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. adjusted clustered by ID)

Notes: Regressions (1) present the simple model, regressions (2) the base specification, and regressions (3) the final model.

I test again the PH assumption, and to consolidate the analysis, I test the assumption for the final model only. None of the regressions fulfil the PH assumption: the values returned for the global PH test are 0.000 in all cases, suggesting that hazards are non-proportional.[31] Age and contract type are stratified and the global PH test results suggest that the stratified Cox model is valid in all three cases.

The coefficients return qualitatively and quantitatively comparable results as in table 5. Irrelevant of the event following employment termination, UISA participation is positive and statistically significant at the 1 per cent level. Participating in the new scheme increases the hazard of workers leaving their current

[31] See table 9 in appendix C.

employment and is quantitatively similar to the previous Cox regressions: the hazard of terminating employment increases by 42.6 per cent if workers change their employment, by 75.6 per cent if workers become unemployed, and by 83.1 per cent if workers become inactive.[32]

Parametric Models

As a last step I fit parametric models and proceed as before. I concentrate on the final model, and test the preferred hazard shape for the different parametric models. The gamma distribution is the preferred model shape for T_1 and T_2, and the log-normal distribution for T_3. As the AIC of the log-normal distribution is only marginally below the AIC of the gamma distribution, I also use the latter shape for T_3.

In table 6 all UISA coefficients are statistically significant at the 1 per cent level. The UISA coefficients return again considerably lower acceleration parameters for unemployment and inactivity: while UISA participation accelerates failure in all cases, the effect is more pronounced if workers become unemployed or inactive after terminating their current employment. The time ratios are 0.705 for employment, 0.563 for unemployment, and 0.535 for inactivity when taking the exponentiated coefficient.

Another interesting aspect is the gender coefficient: women have a lower hazard of terminating employment if the following event is a new employment relation, but have an increased hazard of terminating employment if the following event is unemployment, and especially when becoming inactive. Education is not significant when changing job, it however decelerates time to failure when the following event is unemployment and is significant at the 1 per cent level, while the effect is the opposite for inactivity. The variable hour is only significant when the following event is unemployment and accelerates time to failure. Income is significant in all cases and decelerates time to failure the higher the income category. Household size is significant at the 10 per cent level when becoming unemployed and slightly decelerates time.

[32] See table 11 in appendix D.

Table 6 - Generalized gamma regressions

VARIABLE	T_1 - Employment	T_2 - Unemployment	T_3 - Inactivity
		Acceleration Parameters	
UISA	-0.349***	-0.575***	-0.625***
Female	0.362***	-0.375***	-1.234***
Age	0.006	0.013***	-0.007
Temp. Contract	-0.966***	-1.474***	-1.095***
Education			
- High School	-0.103	0.194*	0.254
- Prof. Formation	-0.280*	0.616***	-0.455
- Univ. and higher	-0.025	0.754***	-0.712**
Hours	-0.002	-0.019***	-0.014
Income			
- 100,000 CLP	0.484*	-0.075	-0.390
- 200,000 CLP	0.811***	0.178	0.294
- 300,000 CLP	0.980***	0.477	1.054
> 300,000 CLP	0.903***	0.891**	1.423*
Household Size	0.017	0.034*	0.036
_cons	3.163***	4.885***	7.109***
/ln_sig	0 .497***	0.465***	0.820***
/kappa	-0.624***	-0.209	-0.410
sigma	1.644	1.592	2.270
Log Likelihood	-1,913	-1,817	-876
AIC	3,857	3,666	1,783
Wald Test Education	0.362	0.001	0.003
Wald Test Income	0.002	0.001	0.000
Employment Exit	741	689	240
At Risk	63,427	63,427	63,427
N	2,006	2,006	2,006

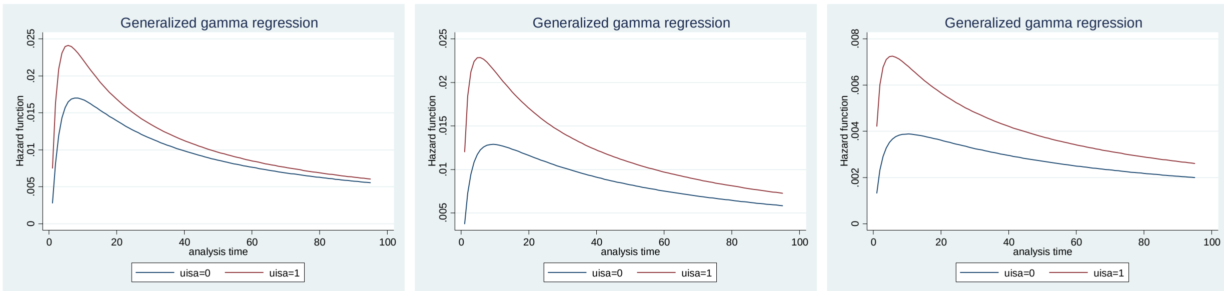
* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. adjusted clustered by ID)

Notes: All regressions are based on the final model.

In figure 5 I compare the hazard functions by UISA participation, and in all cases UISA participants have a higher hazard of terminating employment, irrespective of the following event. The shape is comparable, with a steep hazard increase during the first months of employment, a peak after the first year, and a steady decline thereafter.

Figure 5 - Hazard functions by UISA

(a) T_1 - Employment **(b)** T_2 - Unemployment **(c)** T_3 - Inactivity



Notes: Hazard functions are performed on the final model.

7 Concluding Remarks

This paper analyses the impact of UISA on employment duration in Chile and was motivated by two questions: (i) whether the introduction of UISA has an effect on employment duration and therefore on labour mobility, and (ii) on the magnitude of this effect. Due to changes in labour market conditions, benefits increased in case of unemployment or inactivity, and opportunity costs decreased for employment change, resulting in less costly employment termination. Based on my results, I conclude that UISA participation significantly affects employment duration, characterized by an increased hazard ratio of exiting the current employment in the Cox regressions, and by accelerated time to failure in the parametric models.

In the simple Cox regression the hazard is elevated by 31.4 per cent for UISA participants, while the difference amounts to 67.7 per cent in the final model. The results of the stratified models are similar: the final model, for example, increases the hazard ratio by of 71.8 per cent. The parametric models, based on the generalized gamma distribution, return qualitatively the same result as the Cox model: time to failure is accelerated if workers participate in UISA. The time ratio returns a coefficient of 0.627 for UISA participants in the final model, suggesting that time to failure is 37.3 per cent lower than before the introduction of UISA.

The results of the competing-risk analysis using the final model are summarized as follows: in the Cox model the hazard of leaving employment increases by 45.5 per cent if the following event is another employment relation, by 90.6 per cent if workers become unemployed, and by 65.5 per cent if workers become inactive. For the stratified Cox models the hazard rates increase by 42.6, 75.6, and 83.1 per cent, respectively. The parametric generalized gamma regressions return qualitatively comparable results, where time is accelerated for all following events if workers are UISA participants. The time ratios are

0.705, 0.563, and 0.535, respectively, suggesting that time to failure is 29.5 per cent lower for employment and approximately 45 per cent lower for unemployment or inactivity as the next event, compared to workers with the same next event not participating in the scheme.

Taking reduced employment duration as an indicator for higher labour market flexibility, these results suggest that the policy led to its desired outcome of tackling previously more rigid labour markets. UISA can therefore present an alternative for emerging economies that seek to improve rigidities and to allow for a more dynamic labour market, while avoiding some problems related to unemployment insurance (e.g. moral hazard). Further research may focus on a more detailed examination of the UISA design, for example on the effect of specific scheme requirements after which workers become eligible to withdraw accumulated benefits.

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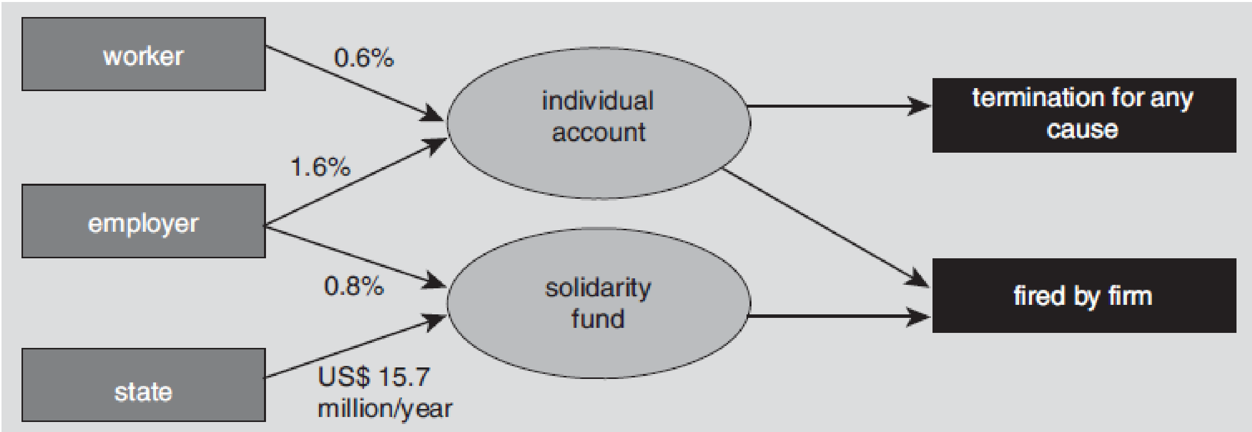
A Appendix: Overview UISA Scheme

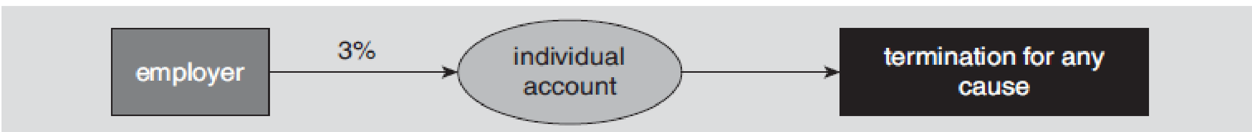
Contribution scheme to individual savings accounts and the solidarity fund:

Figure 6 - Workers with open-ended contracts



Source: Berstein, Fajnzylber and Gana (2012).

Figure 7 - Workers with temporary contracts



Source: Berstein, Fajnzylber and Gana (2012).

B Appendix: Descriptive Statistics

Table 7 - Summary statistics

VARIABLE	Obs	Mean	Std. Dev.	Min	Max
Dummy Variables					
Temporary Contract	2,323	0.50	0.50	0	1
Female	2,323	0.38	0.48	0	1
Knowledge of UISA	2,323	0.22	0.42	0	1
Metropolitan Region	2,323	0.36	0.48	0	1
UISA	2,323	0.36	0.48	0	1
Married	2,210	0.56	0.50	0	1
Categorical Variables					
Education Categories	2,319	1.90	0.83	1	4
Income Categories	2,032	3.09	0.83	1	5
Next Event	1,980	1.76	0.71	1	3
Continuous Variables					
Age	2,323	33.15	11.39	18	74
Children	2,323	0.89	0.74	0	8
Employment Duration	2,323	28.64	29.26	1	95
Firm Size	2,294	18.76	282.75	1	12,000
Hours	2,296	48.48	8.47	2	84
Household Size	2,323	4.77	2.09	1	24
Risk Aversion	2,293	5.48	3.18	0	10
Working Household Members	2,323	0.98	0.97	0	7

Data manipulation: 16 hours observations changed to missing, as workers reported to work over 84 hours per week.

C Appendix: Test of Proportional Hazards Assumption

Multiple Cox regression

Table 8 - Test of proportional hazards assumption

Time: Log(t)

VARIABLE	Base Specification	Final Model	Interactions
		Schoenfeld Residuals	
UISA	0.819	0.001	0.978
Female	0.039	0.081	0.149
Age	0.034	0.036	0.022
Temp. Contract	0.000	0.000	0.000
Education			
- High School	0.556	0. 759	0.630
- Prof. Formation	0.833	0.956	0.476
- Univ. and higher	0.701	0.159	0.058
Hours		0.069	0.108
Income			
- 100,000 CLP		0.017	0.002
- 200,000 CLP		0.002	0.000
- 300,000 CLP		0.000	0.000
> 300,000 CLP		0.001	0.000
Household Size		0.188	0.278
UISA x Temp. Contract			0.413
UISA x High School			0.370
UISA x Prof. Formation			0.970
UISA x Univ. and higher			0.584
Global Test	0.000	0.000	0.000

Competing-risk

Table 9 - Test of proportional hazards assumption

VARIABLE	T_1 - Employment	T_2 - Unemployment	T_3 - Inactivity
	Schoenfeld Residuals		
UISA	0.694	0.018	0.016
Female	0.087	0.031	0.238
Age	0.581	0.309	0.000
Temp. Contract	0.000	0.000	0.005
Education			
- High School	0.117	0.446	0.101
- Prof. Formation	0.089	0.315	0.355
- Univ. and higher	0.237	0.472	0.000
Hours	0.199	0.158	0.474
Income			
- 100,000 CLP	0.182	0.753	0.594
- 200,000 CLP	0.032	0.876	0.458
- 300,000 CLP	0.024	0.616	0.332
> 300,000 CLP	0.040	0.870	0.095
Household Size	0.327	0.186	0.123
Global Test	0.000	0.000	0.000

Notes: the PH test is performed on the final model.

D Appendix: Stratified Cox Model

Table 10 - Stratified Cox model

VARIABLE	Base Specification	Final Model	Interactions
	Coefficients		
UISA	0.255***	0.541***	0.589***
- UISA marg. effect			0.518***
Female	0.265***	0.2160**	0.196***
Age	-0.005***	-	-
Temp. Contract	-	-	-
Education			
- High School	-0.180***	-0.144**	-0.037
- Prof. Formation	-0.227**	0.013	0.120
- Univ. and higher	-0.442***	-0.151	-0.001
Hours		-	0.012
Income			
- 100,000 CLP		-0. 017	-0.020
- 200,000 CLP		-0.274	-0.284
- 300,000 CLP		-0.540**	-0.539**
> 300,000 CLP		-0.561**	-0.582**
Household Size		-0.016	-0.014
UISA x Temp. Contract			0.246*
UISA x High School			-0.260**
UISA x Prof. Formation			-0.262
UISA x Univ. and higher			-0.385
Strata			
Age	-	YES	YES
Contract Type	YES	YES	YES
Hours	-	YES	YES
Global PH Test	0.1822	0.8125	0.7166
Log Likelihood	-12,546	-2,417	-2,413
AIC	25,103	4,854	4,854
Pseudo R2	0.003	0.020	0.021
Wald Test Education	0.000	0.107	0.059
Wald Test Income		0.000	0.000
Employment Exit	1,976	1,691	1,691
At Risk	66,484	63,986	63,986
N	2,319	2,028	2,028

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

Competing-risk

Table 11 - Stratified Cox model

VARIABLES	T_1 - Employment	T_2 - Unemployment	T_3 - Inactivity
		Coefficients	
UISA	0.355***	0.563***	0.605***
Female	-0.345***	0.368***	1.251***
Age	-	-	-
Temp. Contract	-	-	-
Education			
- High School	0.113	-0.230**	-0.426**
- Prof. Formation	0.277*	-0.472**	0.238
- Univ. and higher	0.128	-0.740***	0.338
Hours	-0.002	0.017***	0.007
Income			
- 100,000 CLP	-0.591**	0.484	0.773
- 200,000 CLP	-0.784***	0.198	0.143
- 300,000 CLP	-0.979***	-0.114	-0.553
> 300,000 CLP	-0.915***	-0.429	-0.769
Household Size	0.000	-0.015	-0.055
Strata			
Age	YES	YES	YES
Temp. Contract	YES	YES	YES
Global PH Test	0.4307	0.2553	0.4192
Log Likelihood	-1,941	-1,745	-553
AIC	3,904	3,512	1,128
Pseudo R2	0.011	0.035	0.110
Wald Test Education	0.319	0.001	0.002
Wald Test Income	0.002	0.000	0.000
Employment Exit	741	689	240
At Risk	63,427	63,427	63,427
N	2,006	2,006	2,006

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. adjusted clustered by ID)

E Appendix: Extended Sample

The extended sample includes workers starting two years before and two years after the introduction of UISA, in contrast to the sample of the previous analysis that included workers starting one year before and one year after the introduction of UISA. 2,473 workers started their employment in the two years before and 1,814 workers in the two years after the introduction, containing 2,770 individuals.

Using the extended sample regressions (1) to (4) replicate the analysis of 6.2 (semi-parametric Cox model) in table 12, including the simple model, the base specification, the final regression and the regression with interactions. Results are qualitatively comparable with the one-year analysis: UISA participation is statistically significant at a 1 per cent level throughout the regressions, and increases the hazard of leaving employment. Quantitatively hazard rates are lower compared to the one-year sample, the differences are however not large: in the final model, for example, the one-year analysis returns an elevated hazard of 67.7 per cent, while in the two-year analysis the hazard is increased by 54.2 per cent.

Regressions (5) to (8) additionally include year dummies for workers starting one or two years before the introduction of UISA, and one or two years after the introduction. Year dummies for year one or two after UISA introduction are not statistically different from each other and are combined in the UISA variable. The dummy variable "Year Dummy" in the regression output contains workers who started two years before the UISA introduction, with the reference category referring to all workers who started in the year before. Interpreting the regression results, workers who started a new employment two years before the UISA introduction return an elevated hazard rate compared to workers starting a new employment in the year before. UISA participants of year one and two equally return an elevated hazard rate compared to the reference category.

Table 12 - Regression table Cox model

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Coefficients							
UISA	0.202***	0.163***	0.433***	0.470***	0.247***	0.247***	0.473***	0.513***
- UISA marg. effect				0.413***				0.446***
Year Dummy					0.114***	0.225***	0.122**	0.096*
Female		0.279***	0.197***	0.176***		0.278***	0.199***	0.185***
Age		-0.007***	-0.006***	-0.007***		-0.007***	-0.006***	-0.007***
Temp. Contract		1.050***	0.976***	0.830***		1.064***	0.985***	0.848***
Education								
- High School		-0.157***	-0.102**	0.039		-0.150***	-0.099*	0.045
- Prof. Formation		-0.244***	-0.117	0.033		-0.251***	-0.125*	0.024
- Univ. and higher		-0.346***	-0.109	0.041		-0.341***	-0.111	0.034
Hours			0.011***	0.011***			0.011***	0.011***
Income								
- 100,000 CLP			-0.127	-0.153			-0.127	-0.155
- 200,000 CLP			-0.365**	-0.403**			-0.362**	-0.400**
- 300,000 CLP			-0.523***	-0.562***			-0.520***	-0.555***
> 300,000 CLP			-0.629***	-0.661***			-0.620***	-0.647
Household Size			-0.018*	-0.017			-0.017*	-0.019*
UISA x Temp. Contract				0.295***				0.272***
UISA x High School				-0.271***				-0.284***
UISA x Prof. Formation				-0.318**				-0.213**
UISA x Univ. and higher				-0.297*				-0.315*
Log Likelihood	-28,093	-27,514	-22,047	-22,029	-28,090	-27,501	-22,045	-22,310
AIC	56, 188	55,041	44,120	44,092	56,183	55,019	44,117	44,657
Pseudo R2	0.001	0.019	0.022	0.023	0.001	0.020	0.022	0.023
Wald Test Education		0.000	0.213	0.048		0.000	0.216	0.030
Wald Test Income			0.000	0.000			0.000	0.000
Exit	3,654	3,648	2,989	2,989	3,654	3,648	2,989	2,989
At Risk	116,606	116,538	109,905	109,905	116,606	116,538	109,905	109,905
N	4,287	4,281	3,606	3,606	4,287	4,281	3,606	3,606

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

Notes: The year dummy includes all workers who started employment two years before the UISA introduction. The year dummies for year one and two after the policy introduction are not statistically different from each other and are combined in the UISA variable. The reference group are all workers who started a new employment in the year before UISA were introduced.

F Appendix: Control Group - Public Sector Employees

As control group I take a sample of public sector employees and equally separate them by the starting date of their employment, as previously done for the formal private sector employees. Public sector employees were not affected by the policy introduction and can serve as a control group for this analysis. Taking informal workers in the private sector, however, could return misleading results: the policy introduction could lead to a change in the behaviour of informal workers, as formal employment becomes more attractive after the introduction of UISA. For employers the cost of hiring decreases and could possibly increase the number of formal labour relations.

In regression table 13 I use the variable UISA to indicate if the public sector employees started their employment before or after October 2002. 107 employment relations were started before October 2002, 78 after that date, containing overall 172 individuals. Regressions (1) to (4) replicate the analysis of 6.2 (semi-parametric Cox model) including the simple model, the base specification, the final regression and the regression with interactions. In all regressions the UISA variable is not statistically significant, resulting in no significant difference in employment duration between both groups. Regressions (5) to (7) replicate the parametric models of section 6.3, using again the generalized gamma distribution, as the AIC returned the lowest value for this shape. I take the same regressions as before, except of the interaction model: due to the relatively low number of observations, a discontinuous region was encountered and the regression could not be computed. In the parametric models, the UISA variable is equally not significant, resulting in no significant difference in employment duration between both groups.

Table 13 - Regression table Cox model

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Coefficients				*Acceleration Parameters*		
UISA	0.126	0.109	0.274	-0.438	-0.151	-0.066	-0.347
- UISA marg. effect				0.150			
Female		0.150	0.172	0.156		-0.219	-0.109
Age		-0.015*	-0.015	-0.022**		0.022**	0.025**
Temp. Contract		1.368***	1.150***	0.682**		-1.795***	-1.489***
Education							
- High School		-0.307	-0.545*	-0.739*		0.621**	0.785**
- Prof. Formation		-0.678*	-0.959**	-0.439		0.909**	1.012**
- Univ. and higher		0.108	-0.009	0.117		0.335	0.534
Hours			-0.012	-0.014			0.021*
Income							
- 100,000 CLP			-0.130	-0.342			-0.019
- 200,000 CLP			-0.005	-0.281			-0.080
- 300,000 CLP			-0.341	-0.766			0.185
> 300,000 CLP			-0.496	-0.861			0.359
Household Size			-0.136**	-0.140**			0.178***
UISA x Temp. Contract				1.207***			
UISA x High School				0.489			
UISA x Prof. Formation				-1.238			
UISA x Univ. and higher				-0.151			
_const					2.072***	2.642***	0.631
/ln_sig					0.457***	0.357***	0.322***
/kappa					-1.568***	-0.668**	-0.718**
sigma					1.579	1.429	1.381
Log Likelihood	-624	-592	-521	-514	-308	-275	-245
AIC	1,250	1,199	1,067	1,062	625	571	521
Pseudo R2	0.000	0.051	0.058	0.071			
Wald Test Education		0.044	0.053	0.114		0.055	0.060
Wald Test Income			0.794	0.386			0.882
Exit	132	132	119	119	132	132	119
At Risk	6,887	6,887	6,506	6,506	6,887	6,887	6,506
N	185	185	169	169	185	185	169

* p<0.1, ** p<0.05, *** p<0.01 (Std. Err. clustered by ID)

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