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LABOUR MARKET FLOWS IN ARGENTINA
An application of censored quantile regression for duration data

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An application of censored quantile regression for duration data[1]

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(Full draft)

Abstract

Argentina constitutes an interesting case to be analyzed given that during the nineties it reached high growth rates and a more stable macroeconomic environment but also witnessed significant rises in unemployment, inequality and poverty. Moreover, notwithstanding the stabilization of the economy and the reduction of inflation, labour and income instability grew during the decade. Open unemployment reached unprecedented high levels while the incidence of precarious employment also grew. Both phenomena usually led to higher occupational instability, as short-term jobs are typical among those non-registered wage earners. Occupational turnover would also have been stimulated by modifications introduced to labour regulations as the new types of fixed-term -lower cost- contracts and the trial period.

This document analyses the characteristics of labour mobility in Greater Buenos Aires (Argentina) from 1991 to 2002. The main purpose is to study the flows from employment and unemployment identifying those groups of people with the larger occupational turnover and the factors associated to labour instability. In particular, the paper investigates the influence of tenure and personal and occupational attributes, as well as macro variables –in particular, the effect of business cycle–, on the employment and unemployment duration. The analysis is based on censored quantile regression for duration data. This paper is the first attempt to use this econometric technique for labour dynamic in Argentina.

Keywords: employment duration, unemployment duration, turnover, censored quantile regression, Argentina.
JEL: J63, J64

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1. INTRODUCTION

During the post-war period, Argentina registered moderate levels of open unemployment although the relatively important presence of informal and non-registered-wage-earners occupations[2] suggests that certain population groups were subjected to frequent changes in their labour situation. Some of these features changed during the nineties when the urban labour market went through major alterations induced by the shift in the economic regime. In particular, it was significant the rise in open unemployment and the precarization of jobs, developments that usually entail a rise in occupational instability due to the greater presence of short-duration jobs. Turnover could also have been affected by some of the modifications in labour legislation: fixed-term contracts and the trial period were introduced during this decade.

Therefore, instability in the labour market appears as a relevant matter not only to better understand the labour market performance but also when we want to analyze the dynamics of households' welfare. On the one hand, it amplifies incomes fluctuations and thus increases households' vulnerability, towards social risks, especially among the poorer families. On the other hand, the frequent turnover between jobs can negatively affect the degree of social integration and also jeopardize their employability, since it reduces the possibilities of accumulating some sort of training. However, there could be voluntary transitions that imply both a better insertion in the labour market and increases in productivity due to the diffusion of knowledge and a greater labour allocation.

In this paper we analyze exits from one job to different destinations and also exits from unemployment. This is particularly important in a country like Argentina, where there is a very low coverage of unemployment insurance.[3] With regards to the unemployed, a relevant issue is whether an increase in the average duration of unemployment comes from a rise in the duration of already long episodes, or it is rather a homogeneous increase, affecting every segment of duration. The first case could be suggesting the formation of a hard core of unemployed workers difficult to reduce even in the phases of economic growth and unemployment reduction. With respect to the employed, we will analyze, among other aspects, whether the stability gap between registered and non-registered wage earners remains constant or increases with job tenure.

We will not resort exclusively to traditional duration models as they only estimate the impact of the covariates at the centre of the conditional distribution of duration but do not necessarily show the effect they have over the whole distribution, especially in its extremes. Furthermore, these models assume a proportional effect of the explanatory variables, thus implying that the impact of the covariates on the exit rate remains constant in all the different points of the distribution. Therefore, together with complementary log-log models, quantile regression models for duration data are also estimated.

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[2] In this paper "Informality" is used to refer to own-account workers as well as those wage earners employed by small -"informal"- firms (the ILO approach). Non- registered employees are those wage earners not covered by social security (precarious).

[3] Less of 10% of total unemployment perceive unemployment insurance. This fact is at least in part due to the significant percentage of non-registered wage earners and the high occupational instability.

Consequently, this document has two objectives. First, it aims at analyzing the characteristics of labour mobility in Argentina from 1991 to 2002 by studying transitions from occupations and from unemployment in Greater Buenos Aires. In particular, it investigates the influence of tenure and personal and occupational attributes, as well as macro variables on the employment and unemployment duration. Second, it aims at evaluating the validity of the proportional assumption imposed in most of the studies about unemployment duration in Argentina and other countries and to propose the employment of an alternative econometric method for the analysis of this topic. The confirmation of the no-proportional assumption would reinforce the relevance of the methodological approach used here since it is not possible to analyze this phenomenon with the traditional approach of duration models. Hence, the econometric estimation strategy is based in quantile regressions, what allows the flexible modelling of the hazard function.

The paper follows with a review of the literature on the occupational dynamics and the duration of unemployment in Argentina and other countries. Section 3 presents the most important stylized facts with regards to the macroeconomic regime and the labour market performance throughout the nineties. Section 4 specifies the information source. Section 5 presents the econometric estimation methodology. Section 6 discusses the evidence for Argentina related to the behaviour of the baseline hazard function and the covariates effect. Section 7 analyzes the econometric results of the quantile regression. Finally, section 8 presents the conclusions.

2. LITERATURE REVIEW

At least five important stylized facts regarding the occupational dynamics can be derived from the international literature: (1) a high percentage of labour relationships lasts for a long period of time, (2) most of new jobs end very quickly, (3) as a consequence of the previous two, it also appears a negative relationship between the probability of exiting a job and the elapsed duration (Blau and Kahn, 1981; Mincer and Jovanovic, 1981; Farber, 1993). Another implication is a high probability of exiting from short duration jobs. Consequently, long duration jobs can appear only if such probability decreases when job tenure is accumulated. However, it has been shown that in some cases the probability of exit increases first (approximately until three months) and then it decreases systematically (Farber, 1999); (4) there are strong discrepancies in the degree of labour turnover depending on personal characteristics and characteristics of the job; and (5) in many of the countries studied, there have been modifications in the degree of instability over time.

From (1) and (2) comes the idea that the labour market is not a “spot market” where the labour contract between workers and companies is rectified day after day. However, neither it is a static market where the worker starts and ends his labour career in one same company.[4]

There are not many previous studies about labour mobility in Argentine. Galiani and Hopenhayn (2000) use duration models to estimate the conditional probability of exit from both employment and unemployment. They found a greater instability in the

[4] See, for example, Farber (1999) for the US.

second half of the nineties, independently of duration and without a clear pattern of higher increases in certain intervals with respect to others. However, they could not support the hypothesis that labour reforms implemented in the second half of the nineties caused a decrease in the stability of the jobs directly affected. On the contrary, a significant effect over the episodes with a job tenure of up to three months –which coincides with the maximum length of the trial period established in 1995- are identified in another study (Hopenhayn, 2001).

Beccaria and Maurizio (2001)[5] showed that the control of inflation reduced the households' uncertainty with respect to their incomes' expected behaviour but increased labour instability –associated to a great extent to a higher weight of labour precariousness- fully counteracted such effect.

There is also vast international literature about unemployment duration, but few studies exist for Argentina, probably because such phenomenon gained more relevance from the nineties and the data bases needed for this type of analyses became available only at the beginning of that decade. From the methodological point of view, these studies are generally based on semi-parametric specifications of duration models and analyse transitions from unemployment to an occupation. Galiani and Hopenhayn (2000) model the accumulated risk of unemployment from a model based on the Cox proportional form (1972);[6] Arranz *et al.* (2000) estimate a discrete semi-parametric model for men's unemployment exit rates based on a log-logistic specification and Cerimedo (2004) starts from a complementary log-log model for discrete duration data. In all the three cases, the baseline hazard function is modelled in a non-parametric manner through the utilization of dummy variables for the duration intervals.

All these studies confirm the dependence of the unemployment exit rate on duration, and the influence of the covariates. With respect to the former, only in Cerimedo (2004) the exit rate grows during the first months of unemployment to decrease systematically from then on. In none of these studies have corrections for unobserved heterogeneity been included; hence, it is not possible to completely differentiate the negative dependence on the genuine duration of the effect from heterogeneity in the sample. With respect to the effect of the covariates, the studies showed the expected results regarding personal and occupational variables. Cerimedo (2004) also found that the cycle has a positive and significant effect on the probability of exit from unemployment through the creation of jobs in the growing phase, which allows the increase in transitions from unemployment to employment.

As said, models used in all those studies consider a homogeneous effect of the covariates along the conditional distribution of duration, an assumption that appears to be questionable according to some empirical evidence for both Argentina and other countries, at least for some covariates. For example, Koenker and Geling (2001) apply the quantile regression method (QR) as an alternative way of modelling the baseline hazard function and the effect of the covariates in a unified and flexible manner. Koenker and Bilias (2001) use this methodology for the analysis of duration in unemployment when evaluating the impact of different schemes of unemployment

[5] An extension of another paper on the same topic (Beccaria, 2001).

[6] This study also includes an estimation of the conditional probability of exit from employment to unemployment.

benefits. The utilization of QR allows seeing that the impact of insurance appears with greater intensity in the intermediate intervals of duration and less in the extremes.

Lüdemann *et al.* (2005) go further and apply censored quantile regression (CQR) method (introduced by Powel, 1982 and 1986) to the study of unemployment duration in Germany when only right-censored data are available. They find that the increase of the episodes' duration was not generalized and seems to have concentrated mainly in older individuals.

QR where also used for studying unemployment hazard rate, as in Fitzenberger and Wilke (2005). They used the methodology suggested by Machado and Portugal (2002) and Guimaraes *et al.* (2004) and found evidence with respect to the violation of the proportional assumption for some covariates.[7]

Machado *et al.* (2006), also applying the CQR method, estimate the contribution that the changes in the covariates' distribution and in the conditional distribution of duration had in the change in unemployment duration distribution in US. They find that the modifications in the labour force composition are not so important, and that the changes in the duration distribution are mainly due to two opposite effects: an increase in the transitions between jobs and a greater sensitivity of unemployment duration to the rate of unemployment. As a result, the shorter episodes shortened even more, whereas the longer ones became even longer.

Finally, Fitzenberger and Wilke (2007), using censored Box-Cox quantile regression found evidence that the effect of an increase in the benefit's duration is greater in the highest quantiles of the duration distribution.

Summing up, these few and recent studies based on the QR method show the advantages of employing this tool in the survival analyses. For this reason, in this paper we go further in the application of this methodology in order to estimate the effect of certain covariates on the conditional distribution of duration in a flexible manner, without imposing the proportional assumption *a priori*.[8]

3. MACROECONOMIC PERFORMANCE AND LABOUR MARKET DURING THE NINETIES

This section briefly summarizes some characteristics of the labour market performance during the period of analysis, specially those potentially affecting occupational instability.

The late eighties were characterized by high macroeconomic instability; the inflation rates were extremely high –with peaks of hyperinflation in 1989 and 1990– and the GDP was stagnant. Real wages were consequently very low while, on the other hand,

[7] They found that the difference in the exit probabilities between single and married and between winter and summer are not constant along the distribution of the unemployment duration. Bover *et al.* (1996) also found similar results when comparing those with and without unemployment insurance.

[8] Following to Lancaster (1990, chapter 7): "There is no known economic principle that implies that hazard functions should be proportional and the few non-stationary structural transition models that have been derived do not generally lead to proportional hazard models".

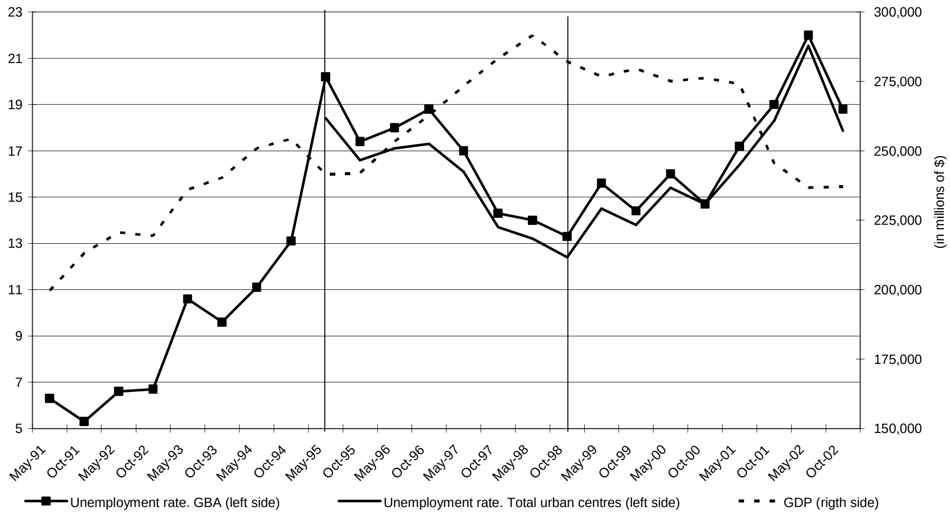
unemployment only grew slowly and remained around moderate levels (around 6%). Such performance was accompanied by growing hourly-underemployment and informality.

In 1991 a new set of short-term policies and structural reforms was implemented. After decades of macroeconomic instability, the "Convertibility Plan" introduced in this year was based on the implementation of a fixed exchange rate, the establishment of the convertibility of the currency in circulation and the prohibition of any issuing of money that was not backed by external assets.[9] Structural reforms were introduced in many fields, including in the labour market, where important modifications to the existing regulations were put into practice since 1991 but, especially, since 1995.[10]

From 1991 onwards, important progresses were made towards macroeconomic stability: inflation was rapidly controlled and GDP grew significantly. During this whole period it is possible to identify three phases with clearly differentiated behaviours regarding macroeconomic and labour market performance. The first one lasted from the beginning of the Currency Board up to 1994; it was characterized by high economic growth rates that only resulted in a weak creation of employment, with lower dynamism than the labour force. This implied a systematic increase of unemployment, which in 1993 had already reached two-digits rates (Graph 1). Although the high growth rates of the first years of the convertibility contributed to the increase of employment in non-tradable sectors, the commercial opening and the exchange rate appreciation seriously attempted against the employment creation in the industrial sector. At the same time, the reduction of the price of capital goods in relation to labour made it possible to incorporate embodied technology to an economy that had registered a low level of investment during the eighties. All this strongly weakened the employment requirements, with the consequent increase of open unemployment rates, even when the economy exhibited, at the beginning of the 90's, a vigorous growth.[11] This process was registered jointly with a rise in the participation rate, which would also have contributed to the increase of unemployment.[12] Together with these two factors, there are other two that contributed to the rise in the unemployment flow: (1) the growth of the exit rates from one occupation as a result of greater labour precariousness, and (2) the weak role played by the informal sector as a refuge from the job loss in the formal sector.

[9] For more details about convertibility, see, for instance, Damill *et al* (2002).
[10] For a description, see Beccaria and Galín (2002).
[11] The manufacturing industry had already started to show an important net loss of jobs since the beginning of the decade: between 1991 and 1994 employment registered a 10% reduction, while output expanded 30%. Between 1991 and the end of 2001 the employment loss was around 40% (data coming from the Industrial Survey).
[12] Between 1991 and 1993 the activity rate in all the urban centres went from 39.5% to 41%. For an analysis of the controversy regarding the causes of this increase, see Altimir and Beccaria (2000).

Graph 1
GDP (at constant 1993 prices) and unemployment rate
May 1991-October 2002



Over the poor *performance* of the labour market, the second phase started with the recession of the middle of the decade (triggered by the Mexican debt crisis), which severely worsened the general conditions of the labour market, raising unemployment to around 20,2% in May 1995 in Greater Buenos Aires (GBA), and 18,4% in total urban centres. Once the external difficulties were overcome, the economy grew again between 1996 and mid-1998, and this time the employment creation grew more in line with the expansion of output. Throughout this second phase the unemployment rate showed a decreasing tendency, although the levels were clearly higher than those of the first phase.

Finally, as from mid-1998 and until the convertibility collapsed, the economy went through a recessionary phase that gave an additional impulse to unemployment growing trend, and dramatically worsened the labour precariousness. In October 2001, the last figure before the macroeconomic regime change, the open unemployment rate in GBA was 19% and 18.3% in all the urban centres as a whole (Graph 1). Unemployment kept growing until May 2002 –as a consequence of the final crisis of the convertibility and the shift in the macroeconomic regime-; from then on, it started to decrease systematically.[13]

The dynamics of unemployment just mentioned were associated to changes in both the entry flows and the average duration of the episodes. In fact, throughout the 1991-2002 period, the rise in the incidence had more to do with the growth of the entry rate (146%)[14] than with the rise in the average duration of the episodes (43%).[15] During the first phase, the rise in unemployment came along with a significant growth of entry

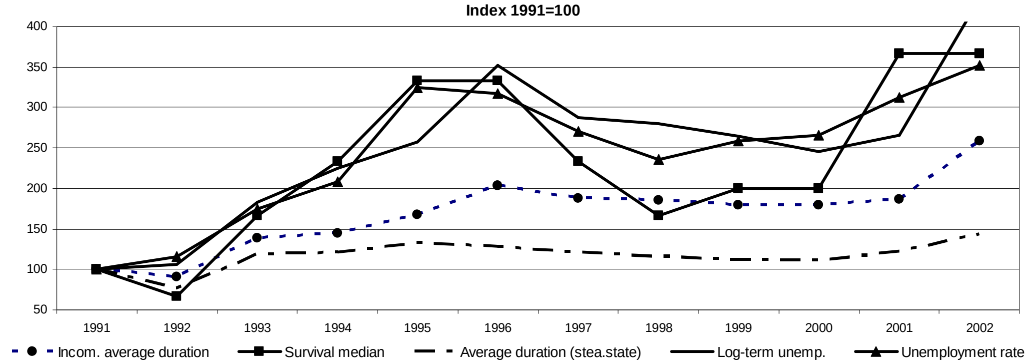
[13] It seems important to highlight the high similarity between the unemployment trends registered in GBA and in all the urban centres as a whole, for which there is data only since 1995 (we discuss this below). This is important because in this paper we focus the analysis on GBA.

[14] The entry rate is computed as the percentage of unemployed with a duration equal or lower than one month over the total labour force.

[15] Under the steady-state assumption, the average complete duration of all the episodes, measured in months, is equal to the ratio between the stock of unemployed and the flow of entry to unemployment (proxied as those unemployed with an up-to-one-month duration). See Layard *et al.* (1991).

rates together with a reduction of exit rates, and thus with an increase in the duration of the episodes. This can be seen in Graph 2, which shows different indicators aimed at capturing the behaviour of duration. In particular the indicators "incomplete duration of the ongoing episodes"[16], the "average complete duration of all the episodes", the "unemployment survival median" and the "percentage of long-term unemployment"[17], they all reflect the growing difficulties that the unemployed workers had to face to leave this state. It seems important to highlight that this rise in duration was registered despite the increase in the entry flow to unemployment which, *ceteris paribus*, should push down the average duration.

Graph 2
Unemployment duration and unemployment rate
Greater Buenos Aires 1991-2002
Index 1991=100



In the second phase, the decline in unemployment rates took place together with a reduction of the complete duration of the episodes and of the survival median. However, the incomplete duration of the episodes and the percentage of long-duration unemployed continued to grow until 1996, and begun to decrease only in the following years. The latter could be due either to the decline of the entry flows or to the fact that in this context of employment growth, the unemployed of shorter duration were able to get jobs quicker than those unemployed of longer duration. Finally, during the recessionary phase (between 1999 and 2002), the increase in the rate of unemployment took place together with a rise in duration, a trend that is shown by all the indicators (although with a lag in some cases).

Therefore, throughout the period an inverse relationship can be seen between the economic cycle and the unemployment rate, except for the first half of the convertibility regime. On the other hand, there is a direct relationship between the unemployment rate and several measures of duration (except for some cases during the second phase), thus indicating an inverse effect between the cycle and the duration of episodes as from the mid-nineties. At the same time, even though the dynamics of unemployment incidence and its duration have had the same sign, the intensity has been different, being higher in the first case. Nevertheless, the proportion of long-term unemployment has also increased significantly. All this evidence serves as a general framework for the more detailed analysis of the changes that took place in the whole distribution of unemployment duration (up to this point we have only analyzed the average duration), which we carry out below.

[16] They are those episodes observed at the moment of the interview.
[17] Defined as the percentage of unemployed with duration of one year or more over all unemployed.

4. SOURCE OF INFORMATION

Data on labour market movements used in this paper come from the regular household survey of Argentina, the Permanent Household Survey (EPH) carried out by the National Statistical Office (INDEC), which covers urban areas and collects information especially on labour market variables. Until 2003, it was carried out twice a year in 28 urban centres, during May and October. The analysis will be restricted to Greater Buenos Aires, given the lack of micro-data for other surveyed areas for the entire period. In order to have enough observations, transitions of the entire period (1991-2002) were pooled.

Although the EPH is not a longitudinal survey, its rotating panel sample allows drawing flow data from it, i.e. a selected household is interviewed in four successive moments or waves. By comparing the situation of an individual in a given and in the following wave (i.e. five or six months later), it is possible to identify if he/she has experienced changes in diverse variables, including occupational variables.

Specifically, the data set used in this paper includes data on the occupational situation in wave *t+1* (October of year *j* or May of year *j*) of persons employed (unemployed) in wave *t* (May of year *j* or October of year *j-1*). Consequently, it is possible to assess whether he/she remained employed (unemployed), became unemployed (employed) or left the labour force.

Data on movements coming from this source face limitations. Some of these derive from the sampling design itself: 25% of the sampling panel is renewed in each wave, thus allowing comparing only 75% of the sample. Yet, this does not hinder the aim of the paper due to the possibility of pooling the data. Nonetheless, it should be taken into account that the effective proportion of individuals and households that are actually matched using panels from two successive waves is lower than 75% due to attrition. Therefore, even if the number of observations left in the pooled panels is still sufficient, the mentioned phenomenon may introduce biases that have not been researched yet. Another difficulty arises from the fact that not every movement can be captured when matching two successive waves because a transition is identified by comparing two observations in a five or seven-month span. Individuals could have performed two or more symmetrical movements during the inter-wave period –e.g. exiting from unemployment to outside the labour force and then returning to unemployment–. Despite the limitations just mentioned, the information to be used seems to provide a reasonable picture of labour market dynamics.

Additionally to using the panel structure of the sample, this paper also resorts to retrospective information in order to apply duration models. Specifically in the case of the employed, we analyze the labour instability of the current employed at the moment of the interview. All those people are asked regarding how long she/he has been at her/his present job, information from which we can build the variable “tenure” –one of the most important variables in labour duration models–. From this information only the incomplete duration of the episode can be drawn. However, the fact of being able to observe the individuals in two successive waves allows knowing which of these episodes comes to an end during the period of observation. In these cases, an approximation of the complete duration can be known. For those episodes still in progress at the time of the second interview, the duration is right censored for the only fact that we know is that the complete duration is at least (i.e. longer than) the elapsed tenure in the last observation.

Also, the same variable "job tenure" *in t+1* is used in order to identify whether a person employed both in *t* and in *t+1* remained in the same job or moved to another one. When individuals who are employed in two successive moments answer "more than five months" (for those interviewed in October) or "seven months" (for those interviewed in May) to the question about job tenure, it is considered that the person did not change jobs. The survey does not investigate the causes associated to job separation; hence, it is not possible to distinguish a dismissal from a voluntary quitting.

A similar procedure was carried out for the unemployed. In this case, it is important to highlight that given the different behaviour of the transitions from unemployment to employment with respect to the exits to inactivity, it does not seem convenient to analyze the exits from unemployment to these two destinies jointly.[18] In addition, given that one of the aims of this paper is to relate the unemployment duration (and the exits from this state) to the economic cycle, it seems convenient to analyze the transitions from this state to employment only.[19]

When studying the exit rates from an occupation, we restricted the analysis to the group of employed between 15 and 65 years old in the case of men, and up to 60 years old in the case of women. The latter are those ages of compulsory retirement in Argentina, and in doing so we try to minimize the bias that could appear with the exits to inactivity of the older individuals. In addition, the study covers the employed individuals that in the first observation declared tenure not higher than 60 months in their job. This subgroup represents approximately 62% of observations, thus allows reducing the effects of the error associated to the measurement of the "tenure" variable, which is concentrated mainly in the higher intervals of duration, as we already mentioned. Finally, we excluded the beneficiaries of unemployment benefits. The final sample has 34,568 observations. In Table A.1 descriptive statistics of the sample are presented. The characteristics of the individuals are those of the first observation.

When studying the exit rates from unemployment we excluded those cases for which durations in this state were not declared. [20] The final sample has 6,525 individuals. The characteristics of the population in the sample are presented in Table A.2.

5. METHODOLOGY

Standard duration models are an econometric technique frequently used in empirical survival analysis. However, in spite of the great utility of these models, they only allow

[18] For example, it can be seen that as time passes in the state of unemployment, the probability of exit to an occupation diminishes, while the probability to enter economic inactivity increases, thus showing markedly different behaviours. This is consistent to what Machin and Manning (1999) point out with respect to the positive dependence of transitions between unemployment and inactivity found in several studies. At the same time, this could be reflecting a certain "discouraged worker" effect or a reduction in the monetary resources for the search of jobs.

[19] The economic cycle could also have an impact on the decision to exit unemployment and enter inactivity. However, due to constraints of space and because it is not central for the aims of this paper we do not analyze this phenomenon.

[20] They represented less than 1% of the sample.

to study the effect of the covariates in the centre of the conditional distribution but not in their extremes. Also, these models impose the proportional-hazards assumption where the covariates affect proportionally the survival function. That is, the effect of the covariates in the exit rate is supposed to be constant throughout the duration time.[21]

Quantile regression (QR) methods are being increasingly used as an alternative to duration models in survival analysis not only in labour studies but also in financial analysis and biometrics, among others. This method allows the specification of the relationship between the covariates and the hazard rates as well as the error distribution in a flexible and robust way. In particular, unlike the Cox model and the Accelerated Failure Time model, QR does not impose a proportional effect of the covariates on the hazard over the duration time, assumptions that may not be empirically valid.

As the classical linear regression method, from which is possible to estimate models for conditional mean functions, QR method proposes a procedure for modelling an entire range of conditional quantiles of distribution, including the median. Following Koenker and Geling (2001), under proportionality assumption, QR models would estimate a family of parallel conditional quantile functions indicating that the covariates only have a pure *location shift* effect, assumption that could be highly restrictive. However, the QR method is more robust and flexible than the proportional hazard model or accelerated failure models, due to its possibility of capturing diverse effects at different quantiles of the duration distribution, allowing identifying different effects of the covariates at different points of the conditional duration distribution.[22]

Nevertheless, in comparison to duration models, QR models have three important drawbacks. On the one hand, QR can not take account of time-varying covariates. On the other hand, unlike mixed proportional hazard models, QR models have not been extended to account for unobserved heterogeneity. Finally, by QR models only simple risks are estimated (where exit rates to all destinations are jointly considered) and no QR framework for competing risks has been developed yet.

In spite of these disadvantages of QR in relation to the alternative duration models, this paper will be based on QR for the modelization of employment and unemployment duration due to the possibilities of this method to capture diverse effects at different quantiles of the duration distribution without imposing any restriction about the variation of estimated coefficients over the quantiles. Also, censored quantile regression allows taking right censoring in the data of duration analysis into account.

The estimation procedure has two parts. First, the changes of quantiles of the conditional distribution of the duration in response to changes of the covariates are estimated following Powell's methodology for the application of QR models with right censoring (Powell, 1984 and 1986). Second, hazard functions are estimated from the application of the simulation method proposed by Machado and Portugal (2002), Guimaraes *et al.* (2004) and Fitzenberger and Wilke (2005).

[21] Proportional Cox Model is a clear example of this specification.
[22] Fitzenberger and Wilke (2007) argument that the application of quantile regression on unemployment duration fits better to non-stationary search models.

5.1 Censored Quantile Regression

As mentioned, in their seminal work Koenker and Basset (1978) introduced QR as a method to obtain a robust estimation of the effect of different covariates over quantiles of the dependent variable.[23]

In order to show how the method works in the survival analysis framework, let y be the unemployment (or employment) duration. This is modelled in a log-linear way, as follows:

$$\ln y_i = x_i^{'}\beta + \mu_i \qquad \text{with } i=1,\ldots\ldots N. \qquad [1]$$

where *x* represents a k covariates vector, β is a k coefficients vector and μ is a random variable with E(μ /x) = 0. From this specification is possible to identify as parameters the effect of the covariates over the conditional mean of the distribution:

$$E(\ln y_i / x) = x_i^{'}\beta_i \qquad [2]$$

These parameters are obtained by OLS (the conventional optimization problem of minimization of the error) or by Maximum Likelihood in the case that some error distribution is supposed.

Similarly, from QR the full range of conditional quantile functions of the log of unemployment (employment) duration are modelled as a linear function of the covariates in each τ -quantile:

$$\ln y_i = x_i^{'}\beta(\tau) + \mu_i(\tau) \qquad [3]$$

In general, given any random variable *t* with continuous and monotonic distribution function F(*t*), the τ -quantile is defined as the value $Q_{(\tau)}$ that satisfies:

$$F(Q_{(\tau)}) = \tau \qquad [4]$$

where τ ε (0,1) and denotes that the τ -quantile is the value of the support of the distribution that accumulates τ % of total observations.

Also, it is supposed that $Q_{(\tau)}(\mu_i / \vec{x}_i) = 0$, that is, the τ -quantile of the distribution of the error conditional to the covariate vector is zero. Therefore:

$$Q_{(\tau)}(\ln y_i / x_i) = x_i^{'}\beta(\tau) \qquad [5]$$

where $Q_{(\tau)}(\ln y_i / x_i)$ denotes the τ -conditional quantile of the logarithm of the duration of the unemployment (employment) given *x*. Therefore, for each covariate a

[23] Here we will not present an exhaustive analysis of quantile regression, and their modification in order to take into account right censoring, but only the most important aspects related to the aims of this paper. For more details about these models, see, for example, Fitzenberger and Wilke (2005), Lüdemann *et al.* (2005).

vector of coefficient $\vec{\beta}(\tau)$ is estimated. Estimation of the parameters $\vec{\beta}(\tau)$ implies resolving following minimization problem:

$$\min_{\beta(\tau)\in R^K} \sum_{i=1}^{n} \rho_{(\tau)}(y_i - x_i^{'}\beta(\tau)) \quad [6]$$

where $\rho_{(\tau)} = z(\tau - I[y_i - x_i^{'}\beta(\tau)]$, I[*] is the "check function" which adopts value 1 if $[y_i - x_i^{'}\beta(\tau)] < 0$ and 0 otherwise.

Finally, equivariance property to monotone transformation of the conditional quantile function allows us re-writing the expression [5] directly in terms of unemployment (employment) duration, given the covariates set:

$$Q_{(\tau)}(y_i / x_i) = \exp(x_i^{'}\beta(\tau)) \quad [7]$$

Until now, complete duration of the spells was supposed from which the coefficient $\beta(\tau)$ can be estimated following to Koenker and Basset (1978). However, data used in this paper does not allow the direct application of this method because of right censoring. Therefore, some modifications are necessary in order to take this fact into account applying censored quantile regression (CQR), as was suggested by Powell (1984, 1986).

Specifically, with right censoring, the observed duration y_i will be determined by $y_i = \min(y_i^*, yc_i)$ being y_i^* the true elapsed unemployment (employment) duration and yc_i the censor point for each spell. Then, CQR is obtained by the minimization of a function similar to [6], as shown next:

$$\frac{1}{N}\sum_{i=1} \rho_{(\tau)}(\ln(y_i) - \min(x_i^{'}\beta(\tau), yc_i)) \quad [8]$$

Powell (1984, 1986) shows that the CQR estimator, $\hat{\beta}(\tau)$, is $\sqrt{N}$-consistent and asymptotically normal distributed. Additionally, [8] is a more general method than the proposed by Koenker and Basset (1978) due to the inclusion of [6] as a special case where $yc_i \to \infty$.

5.2 Hazard function estimation based on Quantile Regression

As mentioned, often in empirical duration analysis it is more relevant to estimate the effect of the covariates on the hazard rate after a certain elapsed duration than the impact of the covariates on duration itself. Therefore, it is necessary to obtain the estimated conditional hazard rates from the quantile regression estimates. Among the different procedures, the one proposed by Machado and Portugal (2002), Guimaraes *et al.* (2004) and Fitzenberger and Wilke (2005) appears as the most appropriate. They have proposed a method of estimation of the conditional hazard function implied by the estimated quantile regression based on a resampling procedure.[24]

In particular, this procedure consists in obtaining empirically the hazard function following three main steps. First, to simulate data based on the estimated quantile regressions for the conditional distribution of the duration T_i. Second, given that "unemployment (employment) duration" is a positive random continuous variable, the density function and the distribution function are estimated directly from simulated duration data. Third, the hazard function for each quantile of conditional distribution is obtained as the ratio between the density function and the survival function (remind that this function is defined as 1 minus the distribution function). Specifically, the procedure is as follows:

a. Generate *M* independent random draws τ_m, m = 1, … , M from a uniform distribution $U(\tau_I, \tau_S)$, where τ_I, τ_S are the bottom and the top limits of distribution support, respectively.[25]
b. For each (τ_m) the QR model is estimated and M vectors $\beta^{\tau m}$ are obtained.
c. For a given value of the covariates x_0 M simulated durations are obtained as:[26]

$$T_m^* = \hat{q}_{\tau m}(T_i \mid x_0) = \exp(x_0' \hat{\beta}^{\tau_m}) \quad with\ m = 1, \ldots, M$$

d. Based on the sample T* the conditional density function $f^*(t|x_0)$ and the conditional distribution function $F^*(t|x_0)$ are estimated.
e. Finally, from the density function and the distribution function, the hazard function is obtained as follows:

$$\lambda_0(t) = \frac{(\tau_S - \tau_I) f^*(t/x_0)}{1 - \tau_I - (\tau_S - \tau_I) F^*(t/x_0)} \quad [9]$$

where the conditional density function is obtained using the kernel estimator:

$$f^*(t \mid x_0) = \frac{1}{Mh} \sum_{m=1}^{M} K\left((t - T^*{}_m)/h\right) \qquad [10]$$

where *h* is the bandwidth and K(.) the kernel function.[27]

6. SOME PRELIMINARY EVIDENCES

6.1 *Job flows*

In this section estimations on the form of the baseline hazard function and on the proportionality of the covariates' effect in the case of employment exit rates are

[24] Following Fitzenberger and Wilke (2005), this procedure is more appropriated than a linear approximation of the hazard rates between the different τ - quantiles.
[25] The limits are chosen in light of the type and the degree of censoring in the data.
[26] This step is supported by Integral Transformation Theorem that implies $T^*_m = F^{-1}(\tau_m)$.
[27] For more detail about kernel estimator for density function, see, for instance, Silverman (1986).

analyzed. This evidence will serve as a reference point for the QR econometric estimations presented in the following section.

With regards to the form of the baseline hazard function, we analyze two types of evidence: one derived from the employment of a non-parametric approach –using the Kaplan-Meier estimator–, and the other coming from the estimation of the complementary log-log models.

Regarding the covariates we bring initial evidences of their impact on hazard rate from the estimation of those models and from the Proportional Cox model, Then, we evaluate the proportional assumption from the test for the model as a whole and for each covariate separately. However, the tests built for this purpose are based on assumptions, which when not valid can lead to misleading conclusions. In order to strengthen the analysis we follow the recommendation suggested by Therneau and Gramsch (2000) of carrying out an additional graphic verification through the relationship of the scaled Schoenfeld residuals (estimated from the Cox model) with a time function. In the case that the proportional assumption does hold, the former do not vary with duration. The contrary will be found when the assumption does not hold.

6.1.1 Baseline hazard function. Exits from a job

In Table 1 we present the exit rates from a given job to any destination: another occupation, unemployment or out of labour force. Such rates correspond to the average values for the period under analysis –between 1991 and 2002- and were calculated for subgroups of employees defined according to the time elapsed in the occupation.

Table 1. Exit rates from a job
Total workers in active ages
Greater Buenos Aires. 1991-2002

	Exit rate to all destinations (%)		
Job Tenure	Average	Intervals 95%	
1 months or less	63.5	61.8	65.0
2 months	51.4	49.3	53.5
3 months	44.9	42.6	47.0
4 to 6 months	36.8	35.2	38.8
7 months to 1 year	30.5	29.4	31.6
More than 1 year to 2 years	21.4	20.6	22.3
More than 2 years to 5 years	16.2	15.5	16.9
1 year or less	41.9	41.1	42.7
More than 1 year to 5 years	18.2	17.7	18.7
Total	29.3	28.9	29.8

From Table 1 we can see a negative relationship between job tenure and the exit rates from it, as Farber (1999) points out.[28] More than 60% of the employed with an elapsed duration lower than one month leaves the job within the one-half of the year between two consecutive observations. On the contrary, only 18.2% -on average- of those with job tenure higher than one year leaves the job. As it was expected –and consistently

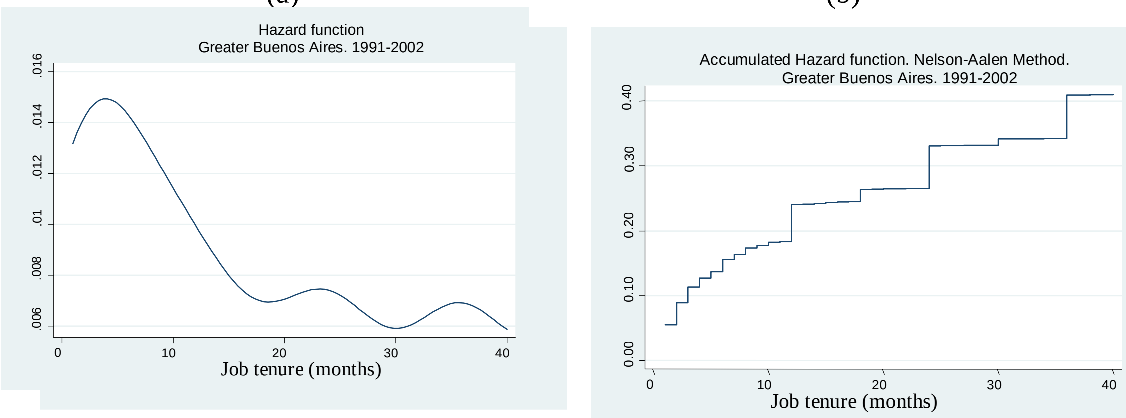
[28] The differences in the exit rates between the duration intervals are all significant at a 95% confidence level.

with the results of many other studies of this type for different countries,[29] including Argentina-[30] duration on the job appears as a very relevant variable to explain differences in exit rates.

Graph 3a shows the estimated hazard function (Kernel-smoothed) from which it is evident the decreasing hazard rate pattern as job tenure grows.[31] In Graph 3b, accumulated hazard function also suggests this behaviour. In particular, the reduction in the hazard rates is especially observed in durations lower than one year: the concavity of this function became clearer in this length of duration indicating that the most important reduction of the job hazard is verified during the first months of the job relationship.

Graph 3
Exit from a job

(a) (b)



This evidence can be showing two types of factors: on the one hand, the presence of negative duration dependence; on the other hand, the effect of observed and unobserved heterogeneity.

With respect to the former, there are three usual arguments that account for the inverse relationship between the exit rate from the occupation and the duration in the job. The first one is related to the role played by specific human capital which, as opposed to general human capital, is provided by the company and builds up with experience. For that reason, the employer –who takes on the cost of this specific training-, will be interested in retaining those employees in whom he has invested. [32] The second argument that can explain the relationship between the job and the exit probability, also related to the models of specific human capital, is the one concerned with the "matching" between the attributes of a given occupation and the actual skills of the worker. Both the employer and the employee don't know each other *ex ante* but rather reveal themselves once in the job. If one of the parties in the labour relationship considers that the other's attributes are below their expectations –i.e. the "matching" is inadequate-, he will decide to end the relationship. Given that usually the information about the occupation and the worker is obtained during the first months, this theory offers an additional explanation to the higher rates of turnover during the first months in

[29] Farber (1999), Kugler (2000), Calderón-Madrid (2000), Saavedra and Torero (2000).
[30] Galiani and Hopenhayn (2000).
[31] This graph also shows certain growth in the probability of exit at the beginning of the job relationship. However this result is not verified in the regressions.
[32] Becker (1975), Oi (1962), Farber (1999).

the job. A third argument is based on the influence of labour regulation –especially the dismissal costs-[33] . As most of the norms directly associate the magnitude of this cost to the job tenure, it becomes a factor that could additionally dissuade the dismissal of personnel with more experience.

With regards to the heterogeneity effect, it is stated that for a given tenure there are differences in total labour turnover among workers with dissimilar characteristics. In particular, the probability of finding those more unstable workers is higher in the first intervals of duration due to these persons have low probabilities of achieving long tenures. The result is that as duration increases, so does the probability of finding more stable people -and thus people with lower exit rates from employment-. Hence, it is necessary to control for these factors to determine if there is genuine duration dependence, as we do below.

In order to confirm this result we have estimated different specifications of the complementary log-log model where the baseline hazard function is modelled in a completely flexible manner through the utilization of dummy variables for the intervals of duration;[34] the results are presented in Table A.3.[35] In all of them the probability of exit from an occupation decreases with the elapsed job tenure. This pattern is observed even when controlling for observed and unobserved heterogeneity[36], which suggests the presence of the usual negative dependence. By comparing regressions I and II we notice that in the second one the coefficients of the duration variables are lower in absolute value. This is a usual result since the fact that we do not include the unobserved characteristics produces a bias in the results towards a greater negative dependence on duration. Even though the results of regression II show that unobserved heterogeneity is statistically significant, the results do not change substantively with respect to regression I.

6.1.2 Effect of the covariates and the Proportional Assumption. Exits from a job

From regression I and II we also conclude that category defines groups of employed with statistically significant differences in their degrees of instability, being this dimension the most important one.[37] Particularly, the exit probabilities are significantly higher for those wage earners with no social security than for registered workers

[33] That includes not only the indemnity values established in some regimes but also those costs of administrative procedures and/or advance notices.
[34] Given that the dependent variable is the conditional probability of exiting employment, a positive sign in the coefficients means higher probabilities of exiting this state.
[35] The application of this model involves transforming the organization of data in order to have as many rows per individual as time periods found in the risk of exit from an occupation. Therefore, the transformed database has a significantly higher quantity of data than the original one.
[36] We tried to take into account the unobserved heterogeneity through the parametric and non-parametric approach, although in the latter case we did not get any result because the verisimilitude function could not be maximized. Hence, in the regression in which we control for heterogeneity, it was assumed that the included term has a Gamma distribution. In the rest of the regressions we did not arrive at any result, even parametrically.
[37] One result also expected has to do with the fact that when we include the correction for unobserved heterogeneity the coefficient value for the rest of the characteristics increases in absolute value, as it happens here.

(baseline group), whereas the stability gap decreases (although it is still positive) when this group is compared to own account workers.[38]

The greater stability of registered workers would be owing to the presence of higher dismissal costs and to the fact that among them we find those workers to which employer give the greater quantity and the better quality of specific human capital. On the other hand, the independent or small-scaled activities –informal-, in which own account workers and non-registered wage earners predominate, are usually subject to events that make them more vulnerable. Besides, investment in fixed capital is low in these activities, which facilitates the interruption of their operation. At the same time, the non-registered wage earners present very low regulatory costs for their dismissal,[39] which makes them attractive for sectors with unstable levels of activity and/or positions. In particular, it could be happen that employers resort to this figure as a substitute for the trial period, or to count on a longer period than the one legally established.

What is also important is that, as regression III of the same table shows, the effect of occupational category does not seem to be proportional, since the exit rates gaps between groups that define this dimension do not remain constant. Rather, the gaps between registered and non-registered wage earners widen as tenure increases. From a methodological point of view, these results would be indicating that the proportional assumption imposed in several models (for example Cox) is not right in this case.

Education is also significant to explain the probability of exit from a given job (regressions I and II). In fact, the latter decreases as the educational level increases, especially for university students, who register a strong reduction in the probability of exiting occupation with respect to those with complete primary school (baseline group). One of the arguments that explain this inverse relationship could be the one mentioned above regarding specific human capital. We need to take into account, on the one hand, that the educational level is closely related to the job qualification and, on the other hand, that the specific and general human capital are usually complementary. Therefore, the more educated workers would receive greater specific training; hence, employers try to retain them more and more as they gain experience in the job. Besides, education increases *per se* the probability of getting better jobs when higher credentials than the ones needed for the job are required. Besides, the more educated workers are more frequently in registered jobs, which are more stable, as it was mentioned above.

Gender and position in the household are also significant variables, which show the expected signs: men and household heads face lower volatility than women[40] and non-household heads (baseline group), respectively (regression I and II). The higher exit probability for women is usually explained by the responsibilities they normally have in certain non-economic activities, according to cultural standards and life cycle. Moreover, these cultural patterns would be reinforced by the fact that employers, on the light of the evidence of women's higher turnover, would discriminate them and give them a higher proportion of unstable jobs than to men with similar characteristics

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[38] On average, in each interval of duration, the non-registered wage earners have an exit probability three times higher than that of the registered wage earners. A value computed as exp(β).

[39] Those coming from the fines and compensations that the employer would have to pay if the dismissed non-registered employee reports the situation to the labour authorities.

[40] As it was mentioned, these results are usual in the international literature. For example, Cerruti (2000) and Rubery *et al.* (1999) arrive at similar results.

(educational level, age, etc. equal to men). However, these results remain in each of the three regressions computed for the groups defined according to categories (regressions IV, V and VI). Therefore, women are not more unstable only because they get more precarious jobs but because they exhibit an exit rate higher than the rest of employees, even in jobs with social security.

Industry does not appear as a very relevant dimension with respect to occupational mobility, since one half of the industries' coefficients are not statistically significant (regression I and II). However, we observe some interesting patterns: as it was expected, construction shows higher turnover than the rest, while the public sector is in the other extreme. It seems peculiar that domestic workers experience less instability than those in the manufacturing activities (control group). Nonetheless, when occupational category is excluded from the regression, the coefficient is no longer statistically significant. Yet it seems necessary to clarify that in this branch, so as in construction, it is difficult to clearly identify the jobs' changes and therefore the results linked to these groups must be interpreted with caution. Finally, the size of the establishment does not appear as important either. Furthermore, contrary to what was expected, the degree of stability does not grow as size increases (regression I and II).

In order to verify the presence of changes in the occupational mobility along the whole period two dummies ("1995-1998" and "1999-2002") were include in the regression. These try to capture the effect of the business cycle as well as of the changes in the labor market and the modification in the labor regulations carried out fundamentally since the second half of this decade.

From the regression I and II it is observed that the coefficients of both dummies are positive and statistically significant indicating that the occupational instability grew in relation to the first years of the nineties (1991-1994 period constitutes the baseline group). This process was verified more intensely among workers with lower job tenure (as shown in regression IX which was estimated only for workers with job tenure equal one year or less). This result is also verified in the regression X where interaction effect between both subperiods and job tenure were estimated. In particular, two dummies variables were incorporated: one of these takes the value 1 in the case of workers with job tenure equal to one year or less during the second subperiod and the other takes the value 1 in the case of workers with this characteristic but in the third superiod. The positive sign of both coefficients confirm again that the raise of the job instability was more intense in the workers with low job tenure.

An increase in the instability gap among occupational categories was also verified, as it can be shown in the estimation performed separately for each of them (regression IV, V and VI). In particular, both subperiod variables resulted negative and significant for registered wage earners whereas the inverse result was obtained in the case of non-registered and non wage earners.

Table A.4 contains Cox proportional model estimations from which the Schoenfeld residuals are obtained, and from which the test of the proportional-hazards assumption is performed (which is shown in Table A.5). As it was mentioned, its null hypothesis is that the variable's effect on the exit rate remains constant along the duration (and thus the effect is proportional). This hypothesis is tested by stating that the correlation coefficient between the scaled Schoenfeld residuals and time is null (ρ_r =0). In Table

A.5 it can be seen that the hypothesis is globally rejected. The hypothesis was also rejected in the case of occupational category (especially in the case of non-registered wage earners), a result that would reinforce the idea of a non-proportional effect of such variables on the exit rate from employment. The same result is verified with the subperiod variables. When analyzing the residuals' graph as a function of time we confirm strong non-linearities, including some of the cases where the test do not reject the proportional-hazards assumption (Graph A.1).

In brief, all of the considered characteristics, except for the size of the establishment contribute to explain the differences in the degree of occupational instability. However, the type of labour relationship appears as the most important variable, followed by education and gender. The effects of all these dimensions tend to reinforce each other, since the non-registered wage earners and, to a less extent, the own account workers concentrate low-skilled jobs. On the other hand, young people are overrepresented within the latter. Also, the gap instability between registered wage earners and the rest of employed increased along the period given that the former reduced their exit rates whereas the latter grew.

Finally, a non proportional effect of the some covariates on hazard rates was found. This evidence strengthens the need to go further in the estimations that capture these differential impacts on the distribution of duration, as we do in the section 7.

6.2 Unemployment flows

Like in the job flows analysis, in this section we starts with the estimations on the form of the base line hazard function and on the proportionality of the covariates' effect in the case of unemployment exit rates.

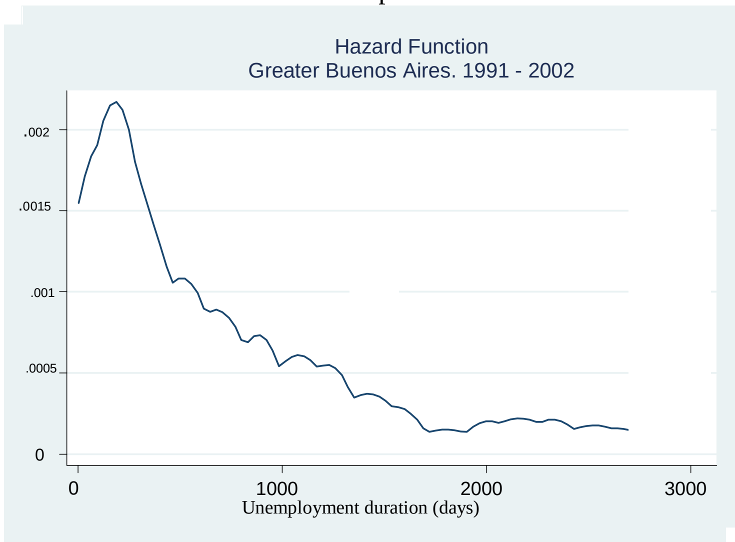
6.2.1 Baseline hazard function. Exits from unemployment

In Graph 4 we present the estimation of the Kaplan-Meier empirical hazard function from which we deduce that the probability of exit from unemployment shows a decreasing trend as duration is accumulated in this state.[41]

The estimations of the complementary log-log models lead us to similar results. The baseline category consists of the unemployed of up-to-one-month duration. The results of the regression are presented in Table A.6. Remember that one important difference between these results and the estimation shown in the graph is that in the latter we were not controlling for the individuals' characteristics and thus the negative relationship could be simply reflecting the observed and unobserved heterogeneity of the sample. With respect to the latter, and following the same strategy that in the case of exit from a job, we carried out two types of estimations: a first one in which we do not control for unobserved heterogeneity (first column of coefficients), and a second one in which the latter is controlled by using a non-parametric mixed model of mass points suggested by Heckman and Singer (1984).[42]

[41] A certain growth in the conditional probability is also noticed in the first interval of duration, although this is not verified in the regressions.
[42] As usual, we assume the existence of two mass points.

Graph 4



From Table A.6 we can see that both estimations show very similar results for all the variables, although the unobserved heterogeneity turns out to be statistically significant. In both cases, the fact that the dummy variables show a more negative value along the intervals of duration[43] would be suggesting –consistently to what we already mentioned– that as unemployment duration is accumulated, the probability of exiting from it diminishes.[44] This behaviour is consistent with that usually found in the studies on unemployment both for Argentina and other countries, as we analyzed in section 2.

6.2.2 Covariates and Proportional Assumption, Exits from unemployment

Given one of the purposes of the paper, it is convenient to clarify that, unlike the employment analysis, the effect of the macroeconomic situation on the probability of exit from unemployment has been here estimated alternatively through the inclusion of different variables: (a) dummy variables representing each wave of the EPH for the period between May 1991 and October 2002[45]; (b) variables corresponding to the three economic phases as in the employment case; (c) the economic cycle[46]; and (d) the aggregated rate of unemployment. Table A.7 contains Cox proportional model estimations from which the Schoenfeld residuals are obtained, and from which the test of the proportional-hazards assumption is performed (which is shown in Table A.8).

Before we examine the test's result it seems convenient to make a first analysis of the covariates' effect on the unemployment exit rate, particularly focusing in those that capture the effect of the economic cycle. There are three important results obtained from

[43] In any case, the reduction in the exit probability is not strictly monotonous decreasing, given that the 10-12-months interval and in the over-18-months interval the exit rates are not lower than the one of the immediately previous interval.
[44] It seems important to highlight that when controlling for unobserved heterogeneity the coefficients that model the dependence to duration decrease in absolute value. This is an expected result, for if we do not take this factor into account, the results overestimate the negative dependence to duration.
[45] Due to the lack of information necessary to build the panels, it was not possible to include the wave of October 1992.
[46] Obtained from the Hodrick-Prescott filter.

alternative (a).[47] On the one hand, it can be seen that the coefficients of the year-wave dummy variables are statistically significant (except for the year 1992), and all of them show a negative sign, thus indicating a reduction in the exit rates with respect to 1991. This was expected, for in that year unemployment registered the lowest value of the series. On the other hand, when the coefficients are analyzed in greater detail, it can be seen that they fit very well the different phases of the economic cycle, especially from the second half of the nineties. In fact, from 1996 to the end of 1998 there is a reduction in the negative gap of exit rates with respect to 1991. From then on, the opposite process develops, especially during the last years of the series, as a consequence of the macroeconomic crisis.

It seems interesting to highlight that in the first phase (until 1994), consistently to what was mentioned, the estimated coefficients show a different behaviour than the business cycle. In particular, in this expansive phase the estimated probabilities of exiting unemployment to employment diminish. On the other hand, these results are compatible to the dynamics of the unemployment rate.

Finally, a strong asymmetry can be seen in the behaviour of exit probabilities given that, despite of during the economic recovery after the 1995 crisis the rates of economic growth were similar to those of the first phase, the probabilities of exiting unemployment were significantly lower. Again, this is correlated to the growing unemployment rates.

This scenery is thus consistent with specification (b), in which the variables indicating the periods are also statistically significant and negative (the baseline category corresponds to the first period). From that specification it follows that in these two phases the probability of exiting unemployment represented, approximately, 75%[48] of the probability experienced in the first half of the nineties. No significant differences are registered between the second and third phase. Moreover, specifications (c) and (d) confirm again the role played by the macroeconomic and labour situation on the unemployment exit rates.

As a result, from the different specifications we can conclude that the business cycle (particularly after the period of structural adjustment) turns out to be a relevant factor in determining the probability of ending of an unemployment spell. This evidence makes it possible to continue analyzing this effect more deeply, based on the QR method. In order to do so, we work with specification (b) only because, on the one hand, the dummy variables for the different phases correctly represent what happened throughout the whole decade; and, on the other hand, because it is a more parsimonious specification than alternative (a) considering the dimension of the coefficient matrix obtained with this method in this specification. Besides, working with dummy variables instead of continuous variables as in the cases of (c) and (d) makes it possible to building empirical hazard functions for each sub period and compare them.

[47] The baseline category is year 1991.

[48] The relative risk is obtained as exp(β). This is the average value, which is assumed to be constant along the conditional distribution of duration.

The rest of the variables included in the regressions (we will not exhaustively discuss its results here) present, in general, the expected signs in all the specifications.[49] Men and household heads have greater probabilities of exiting unemployment than women and non-household heads, respectively. This may be the result of a more active search and a higher acceptance of job offers, given the responsibility they have within the households, especially for household heads. A certain degree of segregation against women could be operating, thus reducing the job offers they get.[50] Age does not present a monotonous relationship with exit rates, where a positive relationship is observed up to 40 years old (which is not always statistically significant) and then a negative relationship is observed, indicating greater difficulties to enter jobs both for young people and for older adults.[51] The presence of little children in the household is associated to higher exit rates, which could be indicating, among other factors, that the need for an income is more pressing for households with children. Similarly, those unemployed that search for jobs to cover the household's basic budget register higher probabilities of getting a job, which could be reflecting the need for a more active search for jobs. Household's income is positively correlated with exit rates, suggesting the positive effect that the existence of financial support could have on job search given the poor coverage of the unemployment insurance in the country.

On the other hand, a higher educational level is associated to lower probabilities of exiting unemployment. Even though a detailed analysis of this result goes beyond the reach of this study, it could be argued that it is related, on the one hand, to an attempt of individuals to get a job that matches their skills. On the other hand, it could be related to the fact that in a context of jobs destruction, the obsolescence of general human capital and, in particular, of specific human capital could have played a role, reducing the probabilities of getting a job. Finally, those unemployed that search for jobs to cover the household's basic budget register higher probabilities of getting a job, which could be reflecting the need to perform a more active search for jobs.

Once the residuals of these regressions are obtained, it is possible to perform the test of the proportional-hazards assumption. In Table A.8 it can be seen that the hypothesis is globally rejected in all the four specifications of the model. However, when the dummy representing each waves are individually evaluated, the hypothesis is rejected in certain month-years only (October 1998, May 2000 and May 2001, in which the coefficient of ρ_r is statistically different from zero) in specification (a) and in the case of the economic cycle variable in specification (c). The hypothesis is not rejected for the period variables in specification (b) and for the unemployment rate in specification (d). Hence, these results seem to be indicating a proportional effect of such variables on the exit rate from unemployment.

However, following the suggestion by Therneau and Gramsch (2000), when analyzing the residuals' graph as a function of time (Graph A.2) we observe again strong non-

[49] The baseline category consists of women, non-household heads, younger than 26 years old, with complete primary school, that do not search for a job to cover the household's basic needs, and live in households with no underage children. We did not include the unemployment insurance among the covariates due to its poor coverage in Argentina. During the nineties, the latter covered less than 10% of the unemployed.
[50] It may be necessary to remember that we are not considering exits to inactivity. Was this destiny included, it could substantially change these results given that women and non-household heads are more intermittent in the labour force.
[51] In the case of young people, the inclusion of exits to inactivity could also alter the results.

linearities in all the cases.[52] Given that the test measures the linear correlation between these two variables, the non-linear relationship would be leading us towards accepting the proportional hypothesis when, in fact, it seems to persist a behaviour in the residuals which, although not captured by these models (and that is not reflected in the test's results), would be indicating that the assumption is not valid, at least in some cases. For the economic cycle variable, where the test made us not accept proportionality, a decreasing linear trend of the residuals is observed, which makes their correlation with time not null.

Hence, the results obtained up to here would be suggesting, on the one hand, a negative dependence on unemployment duration (after controlling for observed and unobserved heterogeneity); on the other hand, a non proportional effect of the business cycle on hazard rates. Like the employment case, this evidence strengthens the need to go further in the estimations that capture these differential impacts on the distribution of duration, as we do in the following section.

7. QUANTILE REGRESSION ESTIMATIONS

7.1 Job flows

The econometric results of the quantile regression for job duration are shown in Graph A.3 which presents the set of coefficients obtained with the different *taus* for each covariate. In addition, for comparison, we present the results of the Weibull model (Table A.9). It is necessary to clarify that unlike the previous results, the dependent variable here is the duration in the given job (as stated in [7]) instead of the exit probability. Consequently we expect the signs of the coefficients to be the opposite of the ones obtained up to here. In particular, a positive sign indicates a higher duration in the job and therefore a lower probability of exit.

7.1.1 Occupational category and employment duration

The Weibull model[53] indicates that the dummy variables for occupational category are negative (and are statistically significant). The QR indicates that the negative sign holds for the coefficients of the different quantiles, thus reflecting that the lower job tenure for non-registered and non-wage earners prevails regardless of the position in the conditional distribution. However, what is more important is that the coefficients' value of each of the two covariates does not remain constant but rather increases in absolute value with the position in the distribution. In particular, the coefficients of the non-registered and non-wage variables became more negative suggesting that the instability gaps with respect to registered wage earners increase with job tenure. That is, as tenure increases, workers in this kind of job reach more stability than the rest of employed people. Firing costs –which rise with tenure and apply only in the case of registered workers– could be a factor associated to this behaviour.

7.1.2 Effects of other covariates

[52] We only include some years of specification (a) as an example.
[53] The control group is the same than in previous regressions.

The results obtained for the rest of the variables used as control are also interesting. In the case of the gender variable the gap in job duration gradually widen suggesting that, while time passes, the probability of exit from a job for men becomes each time lower compared to that of women. A similar behaviour is noticed for household heads.

In the case of education the results of the Weibull model indicate that as education increases the duration in job also does. However, the intensity differs by quantile. In particular, for level complete secondary school or higher it is observed that the duration gaps (with respect to level complete primary) widen with the quantiles suggesting that more educated workers reach job stability more quickly than workers with lower human capital. Remember that the test of proportionality rejected the null hypothesis in the case of complete and incomplete university.[54]

7.2 Unemployment flows

As in the employment analysis, we analyze the coefficients' values for six different *taus*: 0.1, 0.2, 0.4, 0.5 (median), 0.6 and 0.8, in order to obtain econometric results of the quantile regression for unemployment duration (Table A.10).

7.2.1 Business cycle and unemployment duration

Based on the Weibull model[55] we observe that the dummy variables for both periods (1995-1998 and 1999-2002) present a positive sign (and are statistically significant). The QR results indicate that the coefficients' positive sign hold for the different quantiles, thus reflecting the fact that the increase in duration was general for every unemployment spell.[56] However, what is more important is that the coefficients' value of each of the two period variables does not remain constant but rather increases with the position in the distribution. In fact, the coefficients corresponding to the lower quantiles are significantly lower than the superior ones, thus suggesting that the increase in the episodes' duration was verified with greater intensity in the upper extreme of the distribution. This, in turn, means that during the period in consideration long unemployment spells became even longer.

In Graph A.4 we present the set of coefficients obtained with the different *taus* for each covariate. In the case of the variables Period 1995-1998 and Period 1999-2002, the graphs clearly show a growing and significant trend of the coefficients (only in the first quantiles of the variable Period 1999-2002 the confidence interval contains number zero), which allows us to conclude that the worsening of the labour market situation was more severe in spells with long duration unemployment.[57]

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[54] Further analysis is needed in order to test the proportional behaviour of the rest of covariates.
[55] The control group is the same than in previous regressions.
[56] Also here the coefficients turned out to be statistically significant with the only exception of quantile 0.1 for the 1999-2002 period.
[57] In Graph 2 we also present the set of coefficients that correspond to the economic cycle and the unemployment rate. With regards to the former, there seems to be a difference to the panorama just mentioned: even though it can be clearly seen that the effect of this variable is not constant throughout the conditional distribution of the duration, this seems to be more intense in the central part and with less impact in the extremes; i.e. these results suggest that a deterioration of the macroeconomic situation has greater impact not only over the longest durations (consistent with what was mentioned above), but also over the shortest durations. With regards to the unemployment rate, it can be seen that as it increases, it has a more intense impact over the duration of the longest episodes.

One possible explanation for this behaviour could be related to the productive restructuring process that Argentina went through, particularly during the first years of the nineties decade and, as it was mentioned, involved a deep change in the sector pattern of the country's economic growth. Particularly, it could be argued that dismissed workers of the manufacturing sector (especially those with long tenure) were not absorbed by the productive sectors growing in both the first and second phase, and thus they accumulated time in the unemployment. Let us remember that the increase in the duration of the longest episodes had begun to become evident in the second period, when GDP was growing and the unemployment rate was decreasing. Hence, such argument could account for the increase in duration of some episodes even in this expansive phase of the business cycle.

Some of the evidences presented in Table A.11 seem to be consistent with this hypothesis. In the first place, the table shows the distribution of the unemployed by the last job's industry and by the duration in unemployment. There can be noticed a strong rise in the proportion of the unemployed with a two-or-more-years duration coming from the manufacturing industry over the total of unemployed with the same duration. In fact, this is the activity sector that experiences the biggest changes in this indicator. The opposite happens with the shorter episodes of unemployment (one year or less), within which the manufacturing activities gradually lost importance; this could be associated to the reduction in the stock of employed in the manufacturing industry. On the other hand, the Table A.11 shows the variations in the median and other percentiles of duration in unemployment by sector between 1991-1994 and 1995-1998. It can be seen that the major increases occur in manufacturing, especially in the superior percentiles. Then, both indicators would be accounting for the greater relative difficulties to get a job that the individuals previously employed in the manufacturing industry face; this would have contributed to the higher duration of these unemployment episodes.

From the methodological point of view, the evidence obtained from the application of QR would be indicating that the proportional assumption is not confirmed by the data. Hence, the results obtained from duration models are not representative of what happened in the different intervals of duration in unemployment in the period considered.

Finally, as indicated in section 5, once the conditional duration based on the regressions per quantiles is estimated, it is possible to obtain the empirical hazard functions for each of the covariates.[58] In Graph A.5 we present only some of them. In each graph we compare the probabilities of exiting unemployment for two individuals that are equal in all the observable attributes except for the one that is being evaluated. In order to do so, it was necessary to define the set of characteristics on which those functions are estimated. The effect of the period variables was estimated separately for men and women. In both cases it can be clearly seen that the hazard functions are not parallel but they rather present very different behaviours. In particular, the gap in the exit rates between the first period, on the one hand, and the other two, on the other hand, does not remain constant but rather increases with duration in the first intervals, with certain

[58] For the estimation of the density functions needed to build the hazard functions we chose to use an adaptative kernel Epanechnikov with an optimum bandwidth.

fluctuations.[59] Moreover, the most important differences are verified between the first years of the nineties and the rest of the period, while the hazard functions of the second and third phase are very similar.

7.2.2 Effects of other covariates

The results obtained for the rest of the variables used as control are also interesting. In the case of the gender variable the gaps in unemployment duration between men and women gradually widen, while the smallest differences can be seen in the inferior bound of the distribution. This means that in the first months of unemployment the differences between men and women are not very important, while as time passes, the probability of getting a job for a man becomes each time higher compared to that of women.

A similar behaviour is noticed for household heads, although in this case we observe a certain gap reduction in the superior quantiles. In the case of age there is a shift in the sign of the coefficients: these are generally negative at the beginning and then become positive; also, many of them are not statistically significant. In any case, the significance is greater in the higher quantiles and in the superior intervals of age. It is worth to remember that the proportional test rejects this hypothesis for many age intervals in the different specifications.

When it comes to education, the results of the Weibull model indicate that as education increases the duration in unemployment also does, as in the previous regressions. However, the intensity differs by quantile. In general, for level complete secondary school or higher it is observed that the duration gaps diminish as the quantile increases. Under the reservation wages assumption or the search for a better *matching*, these results would be suggesting that these factors have a stronger impact in the first intervals of duration. The results are also consistent with those of the test indicating the non acceptance of the proportionality for the complete secondary school or higher educational level.

Finally, both for the case of family incomes and the reason for searching for a job, it is observed that the gaps diminish along duration. In the first case, this could be indicating that higher household incomes make it possible to do a more active search in the first months of unemployment but that the availability of financial resources decreases its impact as time passes in this state. In any case, the differences between quantiles do not seem to be very important. In the second case, this means that the differences in the intensity of the search according to the motive of the search are stronger during the first months in unemployment and then they diminish. In both cases, the test indicates no proportionality.

[59] In any case, the graphs do not seem to strictly reflect the results of the regressions since the hazard functions for the sub periods cross each other, whereas no changes in sign of the different quantiles' coefficients were seen. The reason of this behaviour in the graph seems to come from the estimation of the kernel density functions and, in particular, in the fact that this function's values for the first period get close to zero much faster than in the subsequent periods, thus indicating that in the former period the duration of the unemployment spells were shorter. This would be causing the functions to cross each other.

8. CONCLUSIONS

Occupational mobility analysis gives information about one of the important dimensions in the Argentinean labour market during the nineties. The evidences about Greater Buenos Aires shown in this paper suggest significant degrees of labour instability across different groups of workers. In particular, non-registered wage earners, low skilled, female and young workers have higher exit rate from a job and higher unemployment duration.

Also, the deterioration in the labour market performance along the decade derived in increasing exit rates from jobs and in unemployment duration. The hypothesis about the differential impact of this worsening across employed and unemployed with different elapsed duration was confirmed: on the one hand, the reduction of the probability of getting a job was larger for individuals in the top extreme in the unemployment duration. Therefore, the long unemployment spells became even longer; on the other hand, the increase in the probability of exit from a job was more intense among workers with lower job tenure.

In the case of unemployment, the empirical evidence suggests that both the productive restructuring process during the first years of the convertibility plan and the macroeconomic instability during the second part of that decade implied an increase in unemployment duration, especially for individuals with more difficulties to get a job even in the positive business cycle subperiod. Most of them, coming mainly from the manufacture sectors, had no access to training programs in order to facilitate their re-insertion to the new productive structure.

In the case of employment, the results from QR also suggest that instability gaps among non-registered/non-wage workers and the registered employees prevail in the all different quantiles but those differences increase with the position in the distribution.

From a methodological point of view, the proportionality assumption is not empirically supported neither in the case of exit from a job nor exit from unemployment. Therefore, we can conclude, similar to other analyses of job or unemployment duration, that the proportional hazard rate assumption is not completely justified in empirical application.

These findings implied the necessity of allowing the estimated coefficients to vary over the quantiles of the duration distribution and to change their sign. Quantile regression appears as a very useful econometric technique for duration analysis.

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ANNEX

Table A. 1
Descriptive statistics of final sample
Total workers
Greater Buenos Aires. 1991-2002

	Total workers				
Covariates	Obs.	Mean	Std. Dev.	Min	Max
Men	34568	0.6065	0.4885	0	1
Household´ head	34568	0.4216	0.4938	0	1
Age					
15 to 25	34568	0.3213	0.4670	0	1
26 to 45	34568	0.4924	0.4999	0	1
More than 45 years old	34568	0.1863	0.3894	0	1
Educational level					
Incomplete primary	34452	0.0758	0.2646	0	1
Complete primary	34452	0.2687	0.4433	0	1
Incomplete secondary	34452	0.2232	0.4164	0	1
Complete secondary	34452	0.1820	0.3858	0	1
Incomplete university	34452	0.1416	0.3486	0	1
Complete university	34452	0.1088	0.3114	0	1
Occupational category					
Non wage earners	34420	0.2371	0.4253	0	1
Registered wage earners	34420	0.4135	0.4925	0	1
Non-registered wage earners	34420	0.3494	0.4768	0	1
Industry					
Manufacture	34568	0.1960	0.3970	0	1
Construction	34568	0.0765	0.2658	0	1
Trade	34568	0.2200	0.4143	0	1
Transport	34568	0.1053	0.3069	0	1
Financial services	34568	0.1054	0.3070	0	1
Personal services	34568	0.0616	0.2405	0	1
Domestic services	34568	0.0818	0.2740	0	1
Public sector	34568	0.0639	0.2446	0	1
Other industries	34568	0.0895	0.2855	0	1
Sub-periods					
1991-1994	34568	0.3199	0.4664	0	1
1995-1998	34568	0.3727	0.4835	0	1
1999-2002	34568	0.3075	0.4615	0	1
Size of the firm					
25 workers or less	32001	0.7345	0.4416	0	1
26 - 100 workers	32001	0.1383	0.3452	0	1
More than 100 workers	32001	0.1272	0.3332	0	1

Table A.2
Descriptive analysis of final sample
Total unemployed
Greater Buenos Aires. 1991-2002

		Observations	Percentage
Final sample		**6,525**	**100%**
Gender			
	Men	4,045	62%
	Women	2,480	38%
Household position			
	Head	2,464	38%
	Other	4,061	62%
Educational level			
	Incomplete primary	691	11%
	Complete primary	2,003	31%
	Incomplete secondary	1,579	24%
	Complete secondary	1,180	18%
	Incomplete university	709	11%
	Complete university	363	6%
Age			
	Younger than 20	1,314	20%
	21-29	1,218	19%
	26-30	686	11%
	31-40	1,138	17%
	41-45	576	9%
	46-50	523	8%
	41-55	460	7%
	Older than 55	593	9%
Sub-periods			
	1991-1994	1,043	16%
	1995-1998	2,948	45%
	1999-2002	2,534	39%
Children in the household			
	Yes	1,851	28%
	No	4,674	72%
Search for jobs to cover the household's basic budget			
	Yes	2,103	32%
	No	4,422	68%
Unemployment duration			
	Equal or less 1 month	1,868	29%
	2 months	998	15%
	3 months	654	10%
	4 months	391	6%
	5 months	358	5%
	6 months	499	8%
	7 months	158	2%
	8 months	157	2%
	9 months	70	1%
	10 months	87	1%
	11 months	21	0%
	12 months	722	11%
	More than 12 months	542	8%
Right censoring		3,242	50%

Table A.3
Exit rate from a job to all destinations
Complementary Log-Log Model
Greater Buenos Aires. 1991-2002

Covariates	Total (Reg. I)	Total with unobserved heterogeneity (Reg. II)	Total (Reg. III)	Non-wage earners (Reg. IV)	Registered wage earners (Reg. V)	Non-registered wage earners (Reg.VI)	Women (Reg. VII)	Men (Reg. VIII)	Workers with job tenure equal to 1 year or less (Reg. IX)	Total (Reg. X)
Baseline hazard										
3 - 6 months	-1.151	-1.119	-1.488	-1.192	-0.658	-1.28	-1.08	-1.193	-1.141	-1.15
	(-30.40)**	(-27.83)**	(-29.11)**	(-15.67)**	(-8.09)**	(-24.34)**	(-18.71)**	(-23.78)**	(-30.13)**	(-30.38)**
Non-registered wage earner			0.256							
			(2.49)*							
6 - 12 months	-1.033	-0.986	-1.342	-0.95	-0.61	-1.195	-0.969	-1.068	-1.02	-1.032
	(-34.73)**	(-27.55)**	(-35.42)**	(-16.78)**	(-9.06)**	(-28.46)**	(-21.15)**	(-27.28)**	(-34.25)**	(-34.70)**
Non-registered wage earner			0.366							
			(4.65)**							
1 - 2 years	-1.544	-1.474	-1.792	-1.378	-1.067	-1.801	-1.496	-1.564		-1.384
	(-48.73)**	(-33.96)**	(-46.42)**	(-24.02)**	(-15.59)**	(-37.48)**	(-30.44)**	(-37.70)**		(-36.45)**
Non-registered wage earner			0.501							
			(8.69)**							
2 - 3 years	-1.604	-1.51	-1.815	-1.375	-1.097	-1.961	-1.568	-1.61		-1.444
	(-40.34)**	(-26.85)**	(-38.49)**	(-20.30)**	(-13.72)**	(-29.37)**	(-25.30)**	(-31.03)**		(-32.12)**
Non-registered wage earner			0.657							
			(12.59)**							
More than 3 years	-1.817	-1.695	-2.003	-1.612	-1.22	-2.26	-1.713	-1.873		-1.655
	(-37.37)**	(-23.91)**	(-35.51)**	(-20.06)**	(-13.36)**	(-25.36)**	(-23.55)**	(-28.59)**		(-31.26)**
Non-registered wage earner			0.719							
			(10.28)**							
Men	-0.211	-0.22	-0.214	-0.262	-0.15	-0.198			-0.212	-0.212
	(-7.59)**	(-7.48)**	(-7.67)**	(-4.72)**	(-2.64)**	(-4.99)**			(-6.36)**	(-7.62)**
Household' head	-0.254	-0.267	-0.296	-0.415	-0.213	-0.144	-0.174	-0.316	-0.234	-0.254
	(-8.88)**	(-8.75)**	(-10.34)**	(-7.71)**	(-3.45)**	(-3.53)**	(-3.42)**	(-8.46)**	(-6.79)**	(-8.88)**
Age										
36 - 45 years old	-0.431	-0.459	-0.463	-0.477	-0.573	-0.358	-0.44	-0.393	-0.449	-0.431
	(-15.75)**	(-14.81)**	(-17.02)**	(-8.63)**	(-10.06)**	(-9.37)**	(-10.98)**	(-10.22)**	(-13.83)**	(-15.74)**
Older than 45 years old	-0.451	-0.483	-0.46	-0.482	-0.661	-0.369	-0.571	-0.332	-0.498	-0.45
	(-12.45)**	(-11.97)**	(-12.73)**	(-7.30)**	(-7.72)**	(-7.05)**	(-10.52)**	(-6.60)**	(-11.35)**	(-12.42)**
Educational level										
Incomplete primary	0.114	0.118	0.128	0.169	0.335	0.011	-0.014	0.177	0.116	0.112
	(2.86)**	(2.79)**	(3.20)**	(2.54)*	(3.02)**	(0.19)	(-0.21)	(3.54)**	(2.46)*	(2.80)**
Incomplete secondary	0.016	0.014	0.005	-0.007	-0.02	0.044	0.124	-0.049	0.023	0.017
	(0.54)	(0.45)	(0.17)	(-0.13)	(-0.28)	(1.12)	(2.59)**	(-1.37)	(0.68)	(0.59)
Complete secondary	-0.279	-0.294	-0.35	-0.438	-0.173	-0.201	-0.128	-0.38	-0.291	-0.277
	(-8.14)**	(-8.07)**	(-10.21)**	(-6.85)**	(-2.37)*	(-3.99)**	(-2.44)*	(-8.21)**	(-7.03)**	(-8.10)**
Incomplete university	-0.352	-0.377	-0.408	-0.432	-0.276	-0.337	-0.204	-0.451	-0.45	-0.351
	(-8.88)**	(-8.82)**	(-10.28)**	(-5.37)**	(-3.45)**	(-5.81)**	(-3.34)**	(-8.39)**	(-9.20)**	(-8.87)**
Complete university	-0.753	-0.777	-0.789	-1.083	-0.381	-0.815	-0.646	-0.808	-0.817	-0.75
	(-13.58)**	(-13.41)**	(-14.28)**	(-9.77)**	(-4.09)**	(-8.18)**	(-8.52)**	(-9.56)**	(-11.45)**	(-13.55)**
Occupational category										
Non-wage earners	0.782	0.804	0.176				0.905	0.686	0.789	0.782
	(21.81)**	(21.01)**	(6.15)**				(16.07)**	(14.56)**	(17.47)**	(21.81)**
Non-registered wage earner	1.152	1.206					1.163	1.162	1.274	1.153
	(36.39)**	(46.35)**					(23.02)**	(28.46)**	(32.59)**	(36.43)**
Industry										
Contrucction	0.678	0.741	0.776	0.555	1.187	0.608	0.511	0.704	0.753	0.679
	(16.69)**	(14.66)**	(19.09)**	(7.14)**	(11.88)**	(10.66)**	(2.34)*	(15.52)**	(15.75)**	(16.70)**
Trade	0.012	0.014	0.017	-0.184	0.098	0.075	0.013	-0.009	0.066	0.013
	(0.36)	(0.38)	(0.51)	(-2.68)**	(1.4)	(1.55)	(0.24)	(-0.19)	(1.61)	(0.4)
Transport	-0.006	-0.006	0.056	-0.123	-0.099	0.031	-0.047	0.014	0.04	-0.005
	(-0.13)	(-0.13)	(1.31)	(-1.3)	(-1.08)	(0.53)	(-0.48)	(0.28)	(0.77)	(-0.12)
Financial services	-0.065	-0.064	-0.083	-0.278	0.243	-0.164	-0.267	0.093	-0.05	-0.065
	(-1.36)	(-1.29)	(-1.75)	(-2.40)*	(3.14)**	(-2.24)*	(-3.62)**	(1.49)	(-0.84)	(-1.37)
Personal services	-0.128	-0.134	-0.164	0.019	-0.133	-0.193	-0.177	-0.13	-0.037	-0.129
	(-2.15)*	(-2.17)*	(-2.76)**	(0.15)	(-1.33)	(-2.05)*	(-2.43)*	(-1.07)	(-0.51)	(-2.18)*
Domestic service	-0.308	-0.319	-0.154	-0.274	-0.333	-0.371	-0.374	0.557	-0.24	-0.309
	(-6.81)**	(-6.66)**	(-3.37)**	(-3.21)**	(-1.12)	(-6.25)**	(-6.59)**	(5.65)**	(-4.47)**	(-6.83)**
Public sector	-0.52	-0.533	-0.59	0.416	-0.515	-0.607	-0.516	-0.494	-0.541	-0.52
	(-6.94)**	(-6.94)**	(-7.94)**	(1.24)	(-5.08)**	(-4.57)**	(-5.17)**	(-4.18)**	(-5.57)**	(-6.95)**
Other industries	-0.058	-0.063	-0.003	-0.158	-0.169	-0.023	-0.074	-0.055	-0.028	-0.059
	(-1.32)	(-1.37)	(-0.07)	(-1.86)	(-1.62)	(-0.39)	(-1.03)	(-0, 89)	(-0.53)	(-1.35)
Period										
1995-1998	0.148	0.157	0.159	0.127	-0.171	0.294	0.048	0.213	0.234	
	(5.60)**	(5.62)**	(6.02)**	(2.59)**	(-3.12)**	(7.62)**	(1.16)	(6.14)**	(7.36)**	
1999-2002	0.162	0.172	0.195	0.367	-0.199	0.191	0.065	0.222	0.218	
	(5.88)**	(5.86)**	(7.05)**	(7.32)**	(-3.35)**	(4.74)**	(1.54)	(6.10)**	(6.53)**	
Less than 1 year (tenure)* 1995-1998										0.232
										(7.32)**
Less than 1 year (tenure)* 1999-2002										0.219
										(6.59)**
Size of the firm										
26 - 100 workers	0.106	0.109	-0.223	-0.144	0.088	0.097	0.037	0.138	0.069	0.107
	(2.64)**	(2.60)**	(5.72)**	(-0.49)	(1.58)	(1.59)	(0.57)	(2.70)**	(1.4)	(2.66)**
More than 100 workers	-0.018	-0.022	-0.39	-0.04	-0.064	0.029	-0.171	0.062	-0.035	-0.017
	(-0.39)	(-0.44)	(-8.62)**	(-0.11)	(-1.05)	(0.36)	(-2.15)*	(1.06)	(-0.6)	(-0.36)
Constant	-2.32	-2.315	-1.555	-1.395	-2.523	-1.199	-2.326	-2.542	-2.46	-2.372
	(-46.63)**	(-44.63)**	(-36.17)**	(-15.44)**	(-26.45)**	(-20.84)**	(-30.39)**	(-42.90)**	(-41.02)**	(-46.34)**
Observations	238,418	238,418	238,418	64,404	113,905	60,109	94,159	144,259	100,388	238,418

Absolute value of z statistics in parentheses
* significant at 5%; ** significant at 1%

Baseline group: workers with tenure lower than 3 months, women, 15 to 25 years old, non household´head, registered wage-earners, with complete primary, period 1991-1994, working in manufacture industries with 25 workers or less.

Table A.4
Cox Proportional Model
Exit rate from a job to all destinations
Greater Buenos Aires 1991-2002

Covariates	**Coefficient**	**p-valor**
Men	-0.2292	0.0000
Household head	-0.2473	0.0000
Age		
36-45 years old	-0.4391	0.0000
Older than 45 years old	-0.4504	0.0000
Educational level		
Incomplete primary or less	0.1216	0.0018
Incomplete secondary	0.0123	0.6600
Complete secondary	-0.2738	0.0000
Incomplete university	-0.3480	0.0000
Complete university	-0.7515	0.0000
Occupational category		
Non-wage earner	0.8024	0.0000
Non-registered wage earner	1.1760	0.0000
Industry		
Construction	0.7032	0.0000
Trade	-0.0103	0.7600
Transport	-0.0162	0.7000
Financial services	-0.0688	0.1400
Personal services	-0.1568	0.0068
Domestic service	-0.3231	0.0000
Public sector	-0.5327	0.0000
Other services	-0.0707	0.0960
Period		
1995 - 1998	0.1526	0.0000
1999 - 2002	0.1714	0.0000
Size of the firm		
26-100 workers	0.0993	0.0120
More than 100 workers	-0.0111	0.8100
Observations		31782

Table A.5
Test of the proportional-hazards assumption
Exit rate from a job to all destinations
Greater Buenos Aires. 1991-2002

Covariates	**rho**	**chisq**	**p-valor**
Men	-0.0167	2.7090	0.0998
Household head	-0.0131	1.5650	0.2110
Age			
36-45 years old	0.0041	0.1540	0.6950
Older than 45 years old	0.0193	3.3570	0.0669
Educational level			
Incomplete primary or less	-0.0137	1.7470	0.1860
Incomplete secondary	-0.0088	0.7080	0.4000
Complete secondary	0.0098	0.8770	0.3490
Incomplete university	0.0400	14.6380	0.0001
Complete university	0.0262	6.5270	0.0106
Occupational category			
Non-wage earner	-0.0184	3.2380	0.0720
Non-registered wage earner	-0.0871	70.6360	0.0000
Industry			
Construction	-0.0611	34.4170	0.0000
Trade	-0.0180	3.0470	0.0809
Transport	-0.0069	0.4450	0.5050
Financial services	-0.0060	0.3350	0.5620
Personal services	-0.0219	4.4860	0.0342
Domestic service	-0.0194	3.7480	0.0529
Public sector	-0.0096	0.8720	0.3500
Other services	-0.0088	0.7160	0.3980
Period			
1995 - 1998	-0.0817	61.9370	0.0000
1999 - 2002	-0.0503	23.7510	0.0000
Size of the firm			
26-100 workers	-0.0049	0.2240	0.6360
More than 100 workers	0.0039	0.1450	0.7040
GLOBAL		**308.5880**	**0.0000**

Table A.6
Complementary Log-Log Model
Exit rate from unemployment to employment
Greater Buenos Aires. 1991-2002

Covariates	Without unob. heterogeneity control	With unob. heterogeneity control
Baseline hazard		
2 months	-0.362	-0.340
	(-6.78)**	(-6.26)**
3 months	-0.565	-0.505
	(-8.96)**	(-7.66)**
4 - 6 months	-0.758	-0.645
	(-14.64)**	(-10.72)**
7 - 9 months	-1.497	-1.311
	(-17.67)**	(-13.65)**
10 - 12 months	-0.098	0.086
	(-1.63)	(1.13)
13 - 18 months	-2.107	-1.769
	(-15.09)**	(-11.28)**
More than 18 months	-1.514	-1.124
	(-19.67)**	(-11.01)**
Men	0.362	0.406
	(8.83)**	(8.6)**
Household head	0.325	0.377
	(5.83)**	(5.84)**
Educational level		
Incomplete primary or less	0.12	0.164
	(1.95)	(2.27)
Incomplete secondary	-0.027	-0.033
	(-0.56)	(-0.59)
Complete secondary	-0.195	-0.247
	(-3.53)**	(-3.9)**
Incomplete university	-0.261	-0.316
	(-3.91)**	(-4.11)**
Complete university	-0.358	-0.411
	(-4.13)**	(-4.13)**
Age		
26 to 30	0.155	0.185
	(2.53)*	(2.64)*
31 to 40	0.045	0.075
	(-0.79)	(1.17)
41 to 45	-0.16	-0.173
	(-2.16)*	(-2.02)*
46 to 50	-0.332	-0.341
	(-4.13)**	(-3.71)**
51 to 55	-0.442	-0.500
	(-5.24)**	(-5.16)**
More than 55 years old	-0.528	-0.547
	(-6.42)**	(-5.83)**
Sub-periods		
1995 to 1998	-0.268	-0.316
	(-5.41)**	(-5.52)**
1999 to 2002	-0.301	-0.331
	(-5.90)**	(-5.65)**
Children in the household	0.193	0.214
	(4.62)**	(4.48)**
Search for jobs to cover the household's basic budget	0.205	0.245
	(4.44)**	(4.51)**
Per capita familiar income	0.000	0.000
	(5.69)**	
Constant	-1.918	-2.899
	(-27.47)**	(-12.25)**
Observations	40,070	40,070
m2		1.286
Constant		(7.8)**
logitp2		0.569
Constant		(1.25)
Prob. Type 1		0.362
		(3.44)**
Prob. Type 2		0.638
		(6.08)**

Absolute value of z statistics in parentheses
* significant at 5%; ** significant at 1%

Baselinte group: women, non household´head, younger than 26 years old, woth complete primary, subperiod 1991-1994, without children in the household, with another reasons for searching, with unemployment duration lower than 1month.

Table A.7
Cox Proportional Model
Exit rate from unemployment to employment
Greater Buenos Aires 1991-2002

Alternative (a)

Covariates	**Coefficient**	**p-valor**
Men	0.3755	0.0000
Household' head	0.3247	0.0000
Educational level		
Incomplete primary or less	0.0911	0.1400
Incomplete secondary	-0.0373	0.4500
Complete secondary	-0.1964	0.0004
Incomplete university	-0.2676	0.0001
Complete university	-0.3667	0.0000
Age		
26 to 30	0.1557	0.0110
31 to 40	0.0703	0.2100
41 to 45	-0.1144	0.1200
46 to 50	-0.3162	0.0001
51 to 55	-0.4183	0.0000
More than 55 years old	-0.4914	0.0000
Month-Year		
May 1992	0.0643	0.7200
May 1993	-0.3545	0.0210
October 1993	-0.4972	0.0016
May 1994	-0.4866	0.0018
October 1994	-0.7493	0.0000
May 1995	-0.6751	0.0000
October 1995	-0.7997	0.0000
May 1996	-0.8247	0.0000
October 1996	-0.7799	0.0000
May 1997	-0.6540	0.0000
October 1997	-0.6289	0.0000
May 1998	-0.6136	0.0000
October 1998	-0.4745	0.0011
May 1999	-0.5651	0.0001
October 1999	-0.6178	0.0000
May 2000	-0.4602	0.0012
October 2000	-0.5500	0.0001
May 2001	-0.9133	0.0000
October 2001	-1.0657	0.0000
May2002	-0.9462	0.0000
October 2002	-0.8221	0.0000
Children in the household	0.1883	0.0000
Search to cover the household's budget	0.2060	0.0000
Per capita familiar income	0.0003	0.0000
Observations		6,525

Alternative (b)

Covariates	**Coefficient**	**p-valor**
Men	0.3646	0.0000
Household' head	0.3252	0.0000
Educational level		
Incomplete primary or less	0.1192	0.0530
Incomplete secondary	-0.0297	0.5400
Complete secondary	-0.2041	0.0002
Incomplete university	-0.2612	0.0001
Complete university	-0.3527	0.0000
Age		
26 to 30	0.1580	0.0096
31 to 40	0.0584	0.3000
41 to 45	-0.1439	0.0520
46 to 50	-0.3186	0.0001
51 to 55	-0.4276	0.0000
More than 55 years old	-0.5070	0.0000
Períod		
1995 - 1998	-0.2514	0.0000
1999 - 2002	-0.2747	0.0000
Children in the household	0.1845	0.0000
Search to cover the household's budget	0.2047	0.0000
Per capita familiar income	0.0003	0.0000
Observations		6,525

Table A.7 (cont.)
Cox Proportional Model
Exit rate from unemployment to employment
Greater Buenos Aires 1991-2002

Alternative (c)

Covariates	**Coefficient**	**p-valor**
Men	0.3754	0.0000
Household' head	0.3389	0.0000
Educational level		
Incomplete primary or less	0.1125	0.0670
Incomplete secondary	-0.0280	0.5700
Complete secondary	-0.1998	0.0003
Incomplete university	-0.2679	0.0001
Complete university	-0.3649	0.0000
Age		
26 to 30	0.1455	0.0170
31 to 40	0.0576	0.3100
41 to 45	-0.1370	0.0650
46 to 50	-0.3278	0.0000
51 to 55	-0.4423	0.0000
More than 55 years old	-0.5344	0.0000
Business cycle	0.0008	0.0000
Children in the household	0.1811	0.0000
Search to cover the household's budget	0.1999	0.0000
Per capita familiar income	0.0003	0.0000
Observations		6,525

Alternative (d)

Covariates	**Coefficient**	**p-valor**
Men	0.3662	0.0000
Household' head	0.3207	0.0000
Educational level		
Incomplete primary or less	0.1040	0.0910
Incomplete secondary	-0.0388	0.4300
Complete secondary	-0.2010	0.0003
Incomplete university	-0.2604	0.0001
Complete university	-0.3597	0.0000
Age		
26 to 30	0.1454	0.0170
31 to 40	0.0597	0.2900
41 to 45	-0.1244	0.0920
46 to 50	-0.3211	0.0001
51 to 55	-0.4305	0.0000
More than 55 years old	-0.5038	0.0000
Unemployment rate	-0.0502	0.0000
Children in the household	0.1896	0.0000
Search to cover the household's budget	0.2127	0.0000
Per capita familiar income	0.0003	0.0000
Observations		6,525

Table A.8
Test of the proportional-hazards assumption
Exit rate from unemployment to employment
Greater Buenos Aires. 1991-2002

Alternative (a)

Covariates	rho	chisq	p-valor
Men	-0.0221	1.5800	0.2090
Household' head	-0.0161	0.8610	0.3540
Educational level			
Incomplete primary or less	0.0013	0.0060	0.9380
Incomplete secondary	-0.0006	0.0010	0.9750
Complete secondary	0.0463	6.9100	0.0086
Incomplete university	0.0474	7.1400	0.0076
Complete university	0.0428	5.8800	0.0153
Age			
26 to 30	-0.0372	4.4600	0.0347
31 to 40	-0.0365	4.4900	0.0341
41 to 45	-0.0309	3.1400	0.0764
46 to 50	-0.0490	7.9900	0.0047
51 to 55	-0.0243	1.9400	0.1640
More than 55 years old	-0.0439	6.4900	0.0109
Month-Year			
May 1992	-0.0315	3.2900	0.0697
May 1993	-0.0149	0.7230	0.3950
October 1993	-0.0155	0.7850	0.3760
May 1994	-0.0244	1.9400	0.1640
October 1994	-0.0186	1.1300	0.2880
May 1995	-0.0187	1.1400	0.2860
October 1995	-0.0089	0.2600	0.6100
May 1996	-0.0207	1.4000	0.2370
October 1996	-0.0115	0.4300	0.5120
May 1997	-0.0175	1.0100	0.3160
October 1997	-0.0200	1.3000	0.2540
May 1998	-0.0326	3.4900	0.0616
October 1998	-0.0408	5.4500	0.0196
May 1999	-0.0228	1.7000	0.1920
October 1999	-0.0248	2.0100	0.1560
May 2000	-0.0355	4.1100	0.0426
October 2000	-0.0232	1.7600	0.1840
May 2001	-0.0506	8.3400	0.0039
October 2001	-0.0201	1.3200	0.2500
May2002	-0.0011	0.0037	0.9520
October 2002	-0.0191	1.1900	0.2750
Children in the household	-0.0075	0.1860	0.6660
Search to cover the household's budget	-0.0390	4.8000	0.0285
Per capita familiar income	-0.0528	5.7000	0.0169
GLOBAL		116.0000	0.0000

Alternative (b)

Covariates	rho	chisq	p-valor
Men	-0.0264	2.2195	0.1360
Household' head	-0.0110	0.4020	0.5260
Educational level			
Incomplete primary or less	0.0008	0.0021	0.9640
Incomplete secondary	-0.0012	0.0043	0.9470
Complete secondary	0.0516	8.5307	0.0035
Incomplete university	0.0493	7.6318	0.0057
Complete university	0.0413	5.4512	0.0196
Age			
26 to 30	-0.0446	6.4134	0.0113
31 to 40	-0.0400	5.3768	0.0204
41 to 45	-0.0324	3.4125	0.0647
46 to 50	-0.0516	8.8463	0.0029
51 to 55	-0.0271	2.3933	0.1220
More than 55 years old	-0.0510	8.7425	0.0031
Períod			
1995 - 1998	0.0041	0.0553	0.8140
1999 - 2002	-0.0149	0.7223	0.3950
Children in the household	-0.0065	0.1413	0.7070
Search to cover the household's budget	-0.0412	5.3822	0.0203
Per capita familiar income	-0.0481	4.5565	0.0328
GLOBAL		95.1364	0.0000

Table A.8 (cont.)
Test of the proportional-hazards assumption
Exit rate from unemployment to employment
Greater Buenos Aires. 1991-2002

Alternative (c)

Covariates	rho	chisq	p-valor
Men	-0.0286	2.5900	0.1070
Household' head	-0.0079	0.2090	0.6470
Educational level			
Incomplete primary or less	0.0005	0.0007	0.9790
Incomplete secondary	0.0003	0.0002	0.9880
Complete secondary	0.0491	7.7400	0.0054
Incomplete university	0.0499	7.8300	0.0052
Complete university	0.0421	5.6800	0.0171
Age			
26 to 30	-0.0423	5.7700	0.0163
31 to 40	-0.0413	5.7500	0.0165
41 to 45	-0.0355	4.1100	0.0426
46 to 50	-0.0540	9.6400	0.0019
51 to 55	-0.0286	2.6700	0.1030
More than 55 years old	-0.0519	9.0300	0.0027
Business cycle	-0.0570	10.4000	0.0013
Children in the household	-0.0072	0.1710	0.6790
Search to cover the household's budget	-0.0439	6.0900	0.0136
Per capita familiar income	-0.0469	4.3700	0.0366
GLOBAL		103.0000	0.0000

Alternative (d)

Covariates	rho	chisq	p-valor
Men	-0.0238	1.7914	0.1810
Household' head	-0.0123	0.5044	0.4780
Educational level			
Incomplete primary or less	0.0016	0.0082	0.9280
Incomplete secondary	-0.0009	0.0027	0.9590
Complete secondary	0.0507	8.2197	0.0041
Incomplete university	0.0477	7.1346	0.0076
Complete university	0.0423	5.6895	0.0171
Age			
26 to 30	-0.0417	5.5973	0.0180
31 to 40	-0.0388	5.0575	0.0245
41 to 45	-0.0319	3.2859	0.0699
46 to 50	-0.0509	8.5739	0.0034
51 to 55	-0.0283	2.6102	0.1060
More than 55 years old	-0.0507	8.6147	0.0033
Unemployment rate	0.0222	1.6762	0.1950
Children in the household	-0.0087	0.2485	0.6180
Search to cover the household's budget	-0.0426	5.7128	0.0168
Per capita familiar income	-0.0511	5.2680	0.0217
GLOBAL		93.4181	0.0000

Table A.9
Weibull Model
Job duration
Greater Buenos Aires. 1991-2002

Covariates	Coefficient	p-valor
Men	0.2914	0.0000
Household head	0.3164	0.0000
Age		
36-45 years old	0.5687	0.0000
Older than 45 years old	0.5878	0.0000
Educational level		
Incomplete primary or less	-0.1562	0.0016
Incomplete secondary	-0.0130	0.7160
Complete secondary	0.3549	0.0000
Incomplete university	0.4554	0.0000
Complete university	0.9634	0.0000
Occupational category		
Non-wage earner	-1.0190	0.0000
Non-registered wage earner	-1.5320	0.0000
Industry		
Construction	-0.8968	0.0000
Trade	0.0051	0.9040
Transport	0.0085	0.8750
Financial services	0.0868	0.1410
Personal services	0.2044	0.0056
Domestic service	0.4238	0.0000
Public sector	0.6802	0.0000
Other services	0.0934	0.0840
Period		
1995 - 1998	-0.1881	0.0000
1999 - 2002	-0.2095	0.0000
Size of the firm		
26-100 workers	-0.1344	0.0078
More than 100 workers	0.0135	0.8180
(Intercept)	4.7194	0.0000

Table A.10
Quantile Regression Model and Weibull Model
Unemployment duration
Greater Buenos Aires 1991-2002

	TAUS						
Covariates	**0.1**	**0.2**	**0.4**	**0.5**	**0.6**	**0.8**	**WEIBULL**
Men	-0.3459 (**)	-0.4371 (**)	-0.5311 (**)	-0.4881 (**)	-0.5137 (**)	-0.5591 (**)	-0.4688 (**)
Household' head	-0.1623	-0.3536 (**)	-0.5319 (**)	-0.5201 (**)	-0.4617 (**)	-0.3880 (**)	-0.4113 (**)
Educational level							
Incomplete primary or less	-0.0410	-0.1140	-0.2872 (**)	-0.1903 (*)	-0.2363 (*)	-0.1583	-0.1378 (*)
Incomplete secondary	0.0351	0.0836	0.0072	0.1568 (**)	0.0145	0.0023	0.0373
Complete secondary	0.3404 (**)	0.4623 (**)	0.3432 (**)	0.3632 (**)	0.2207 (**)	0.0391	0.2502 (**)
Incomplete university	0.5914 (**)	0.5205 (**)	0.4195 (**)	0.4728 (**)	0.3112 (**)	0.2107	0.3635 (**)
Complete university	0.8113 (**)	0.6994 (**)	0.5537 (**)	0.5043 (**)	0.3677 (*)	0.5279 (**)	0.5010 (**)
Age							
26 to 30	-0.2173 (*)	-0.1967 (*)	-0.1903 (**)	-0.1630 (**)	-0.2816 (**)	-0.0756	-0.1801 (**)
31 to 40	-0.3267 (**)	-0.1488	-0.1539	-0.0481	-0.0545	-0.0756	-0.0424
41 to 45	-0.3267 (**)	-0.0777	0.1718	0.3659 (**)	0.3201 (**)	-0.0756	0.2180 (**)
46 to 50	-0.2002 (*)	0.1694	0.3531 (**)	0.4950 (**)	0.5685 (**)	-0.0756 (**)	0.4508 (**)
51 to 55	-0.1517	0.2199	0.7042 (**)	0.7804 (**)	0.8001 (**)	-0.0756 (**)	0.5773 (**)
More than 55 years old	-0.1011	0.0716	0.6081 (**)	0.8894 (**)	1.0749 (**)	-0.0756 (**)	0.7225 (**)
Period							
1995 - 1998	0.1774 (*)	0.2152 (**)	0.4239 (**)	0.3732 (**)	0.4128 (**)	0.3791 (**)	0.3356 (**)
1999 - 2002	0.1193	0.1897 (**)	0.4402 (**)	0.3607 (**)	0.4630 (**)	0.5849 (**)	0.3888 (**)
Children in the household	-0.2580 (**)	-0.2332 (**)	-0.2730 (**)	-0.2840 (**)	-0.2470 (**)	-0.3729 (**)	-0.2486 (**)
Per capita familiar income	-0.0012 (**)	-0.0010 (**)	-0.0007 (**)	-0.0006 (**)	-0.0005 (**)	-0.0005 (**)	-0.0004 (**)
Search to cover the household's budget	-0.3133 (**)	-0.4427 (**)	-0.2880 (**)	-0.3067 (**)	-0.2977 (**)	-0.1693	-0.2668 (**)
Constant	3.7951 (**)	4.4511 (**)	5.2336 (**)	5.5221 (**)	5.8961 (**)	6.6554 (**)	6.0396 (**)
Observations							6,525

* significant at 10%; ** significant at 5%

Table A.11
Industry of the last job (unemployed workers)
Greater Buenos Aires 1991-2002

Distribution of unemployment according industry of their last job (%)

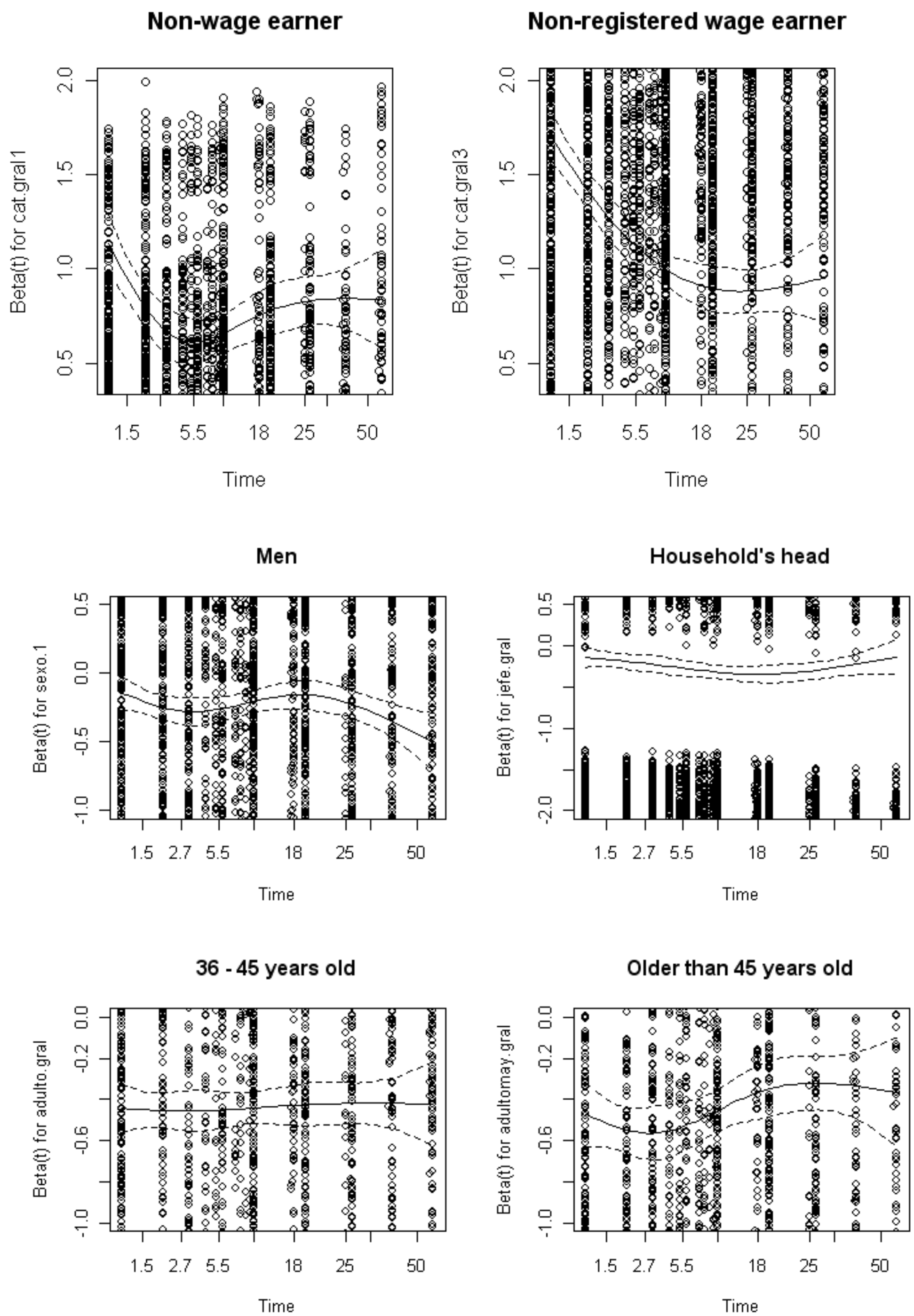
	Total unemployment			With unemp. duration => 1 year			With unemp. duration => 2 year		
Industry	**1991-1994**	**1995-1998**	**1999-2002**	**1991-1994**	**1995-1998**	**1999-2002**	**1991-1994**	**1995-1998**	**1999-2002**
Manufacture	25	20	18	27	25	19	12	26	25
Construccion	17	21	24	10	5	12	36	2	11
Trade	19	19	19	19	24	24	12	23	21
Transport	9	7	7	13	7	7	4	6	4
Finacial services	5	7	7	4	10	7	4	11	6
Educ. and health	1	2	3	3	3	5	8	4	6
Domestic services	8	11	10	8	14	12	24	12	13
Other industries	16	13	12	17	13	14	0	15	13
Total	100	100	100	100	100	100	100	100	100

Porcentual variation of unemployment duration between 1991-1994 and 1995-1998

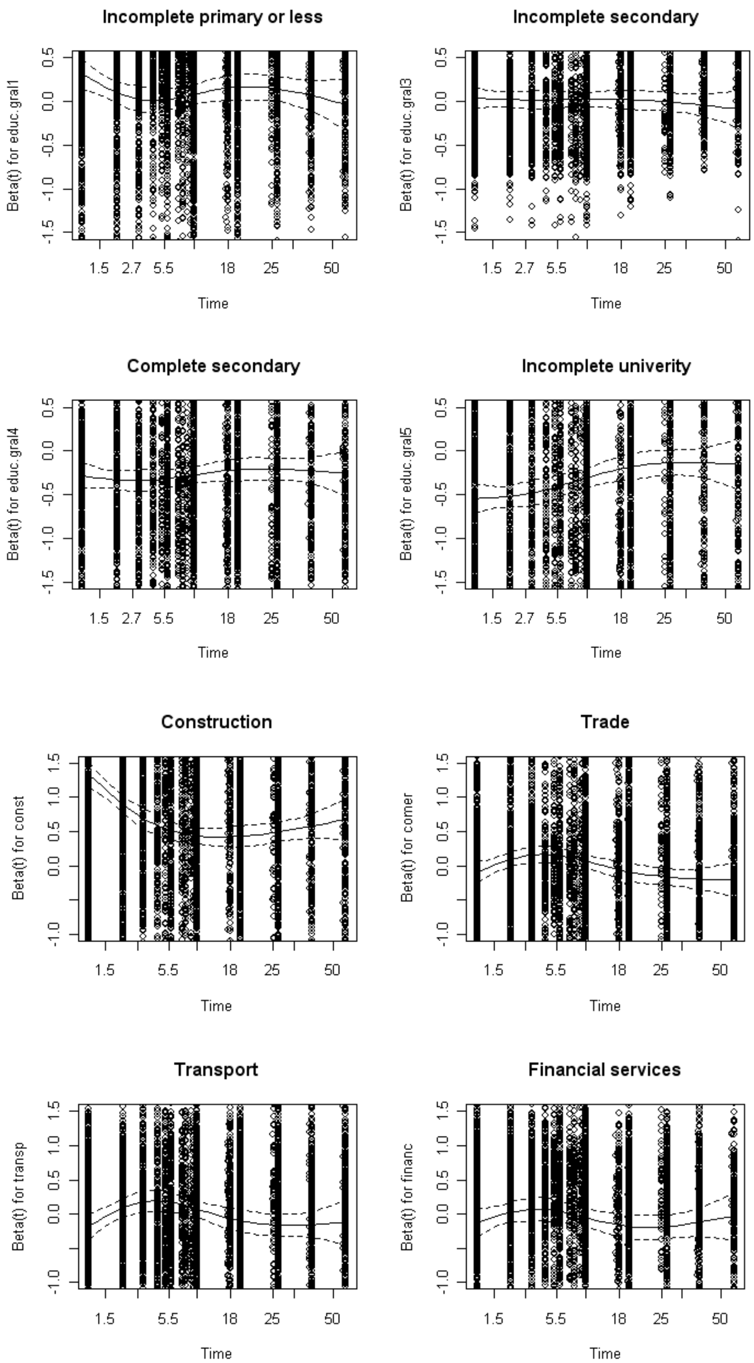
	Industry of the last job					
Percentile	**Manufacture**	**Construcction**	**Trade**	**Transport**	**Financial serv.**	**Educ and health**
1%	75%	0%	0%	-50%	0%	-77%
5%	58%	0%	50%	-14%	0%	-67%
10%	14%	-33%	67%	-50%	40%	-67%
25%	50%	-5%	100%	0%	100%	-67%
50%	33%	50%	33%	0%	13%	-33%
75%	67%	0%	67%	-14%	83%	-53%
90%	17%	-14%	0%	0%	50%	-50%
95%	100%	-25%	0%	33%	50%	0%
99%	100%	0%	50%	-58%	50%	50%
Average duration	61%	-3%	25%	-16%	48%	-37%

Graph A.1

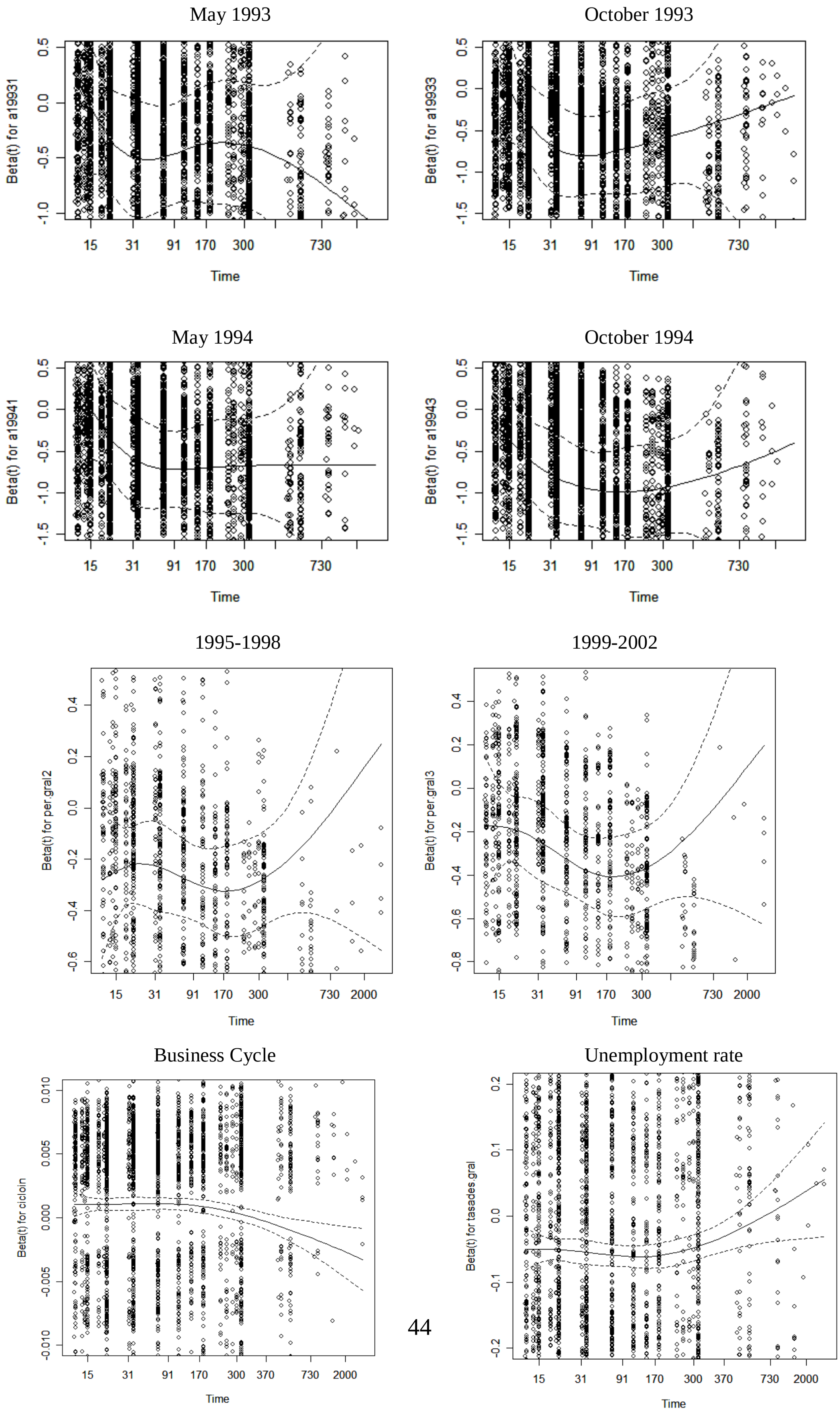
Proportionality test based on the scaled Schoenfeld residuals. Job hazard rate



Graph A.1 (cont.)
Proportionality test based on the scaled Schoenfeld residuals. Job hazard rate



Graph A.2
Proportionality test based on the scaled Schoenfeld residuals. Unemployment hazard rate

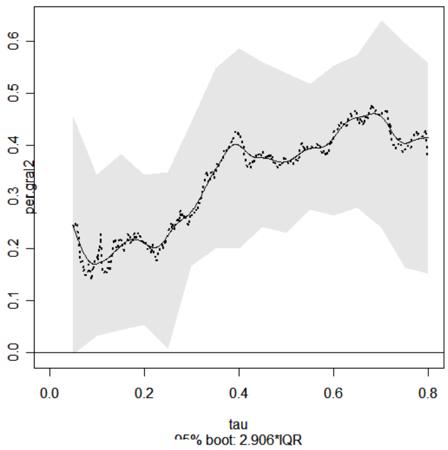


Graph A. 3

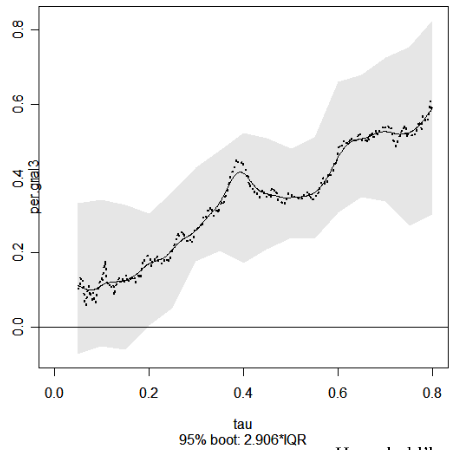
Estimated coefficient from Quantile Regression. Job tenure.

Graph A. 4
Estimated coefficient from Quantile Regression. Unemployment duration

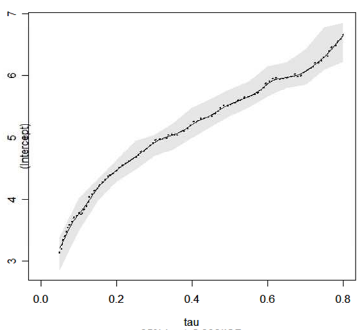
1995-1998



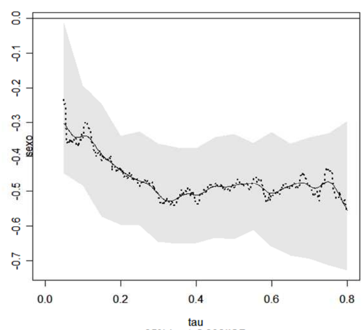
1998-2002



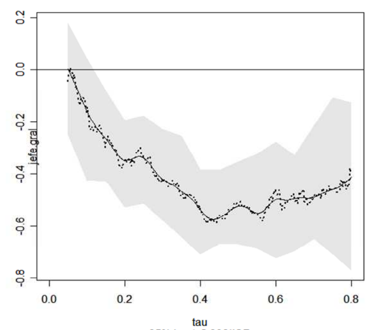
Intercept



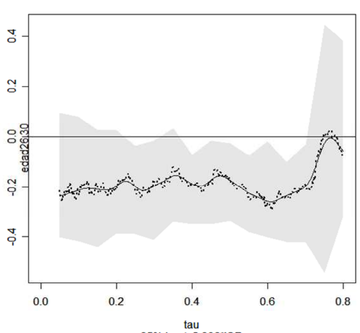
Men



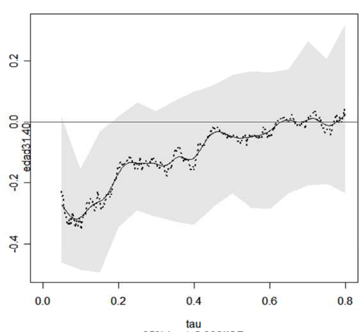
Household'head



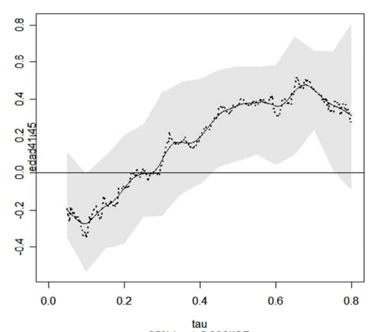
Age: 25-30



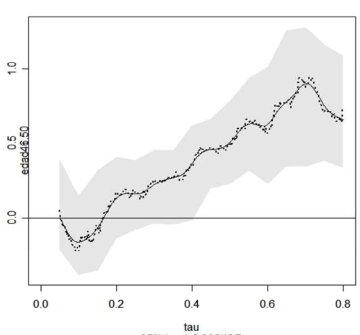
Age: 31-40



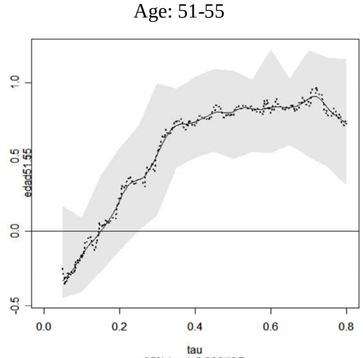
Age: 41-45



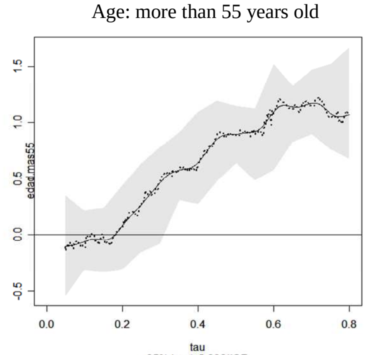
Age: 46-50



Age: 51-55

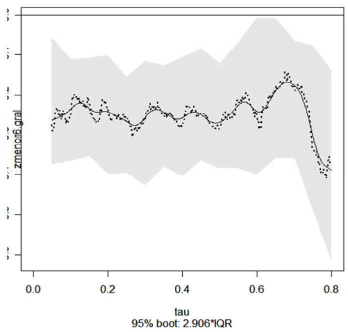


Age: more than 55 years old

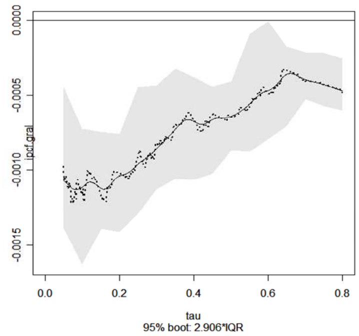


Graph A.4 (cont.)
Estimated coefficient from Quantile Regression. Unemployment duration.

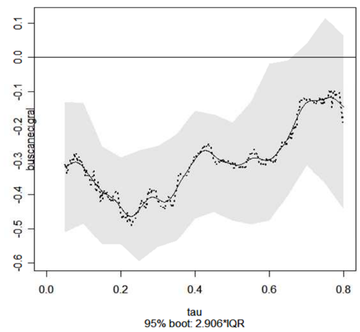
Children in the household



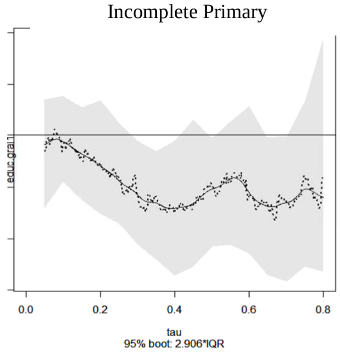
Per Capita Familiar Income



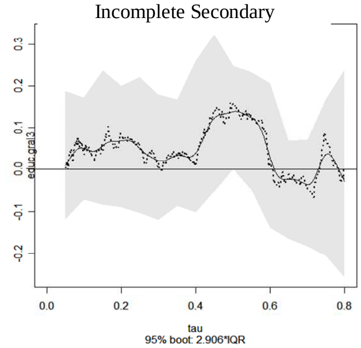
Search to cover the household's budget



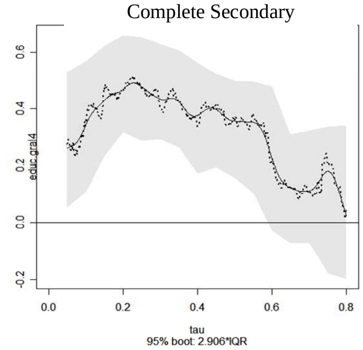
Incomplete Primary



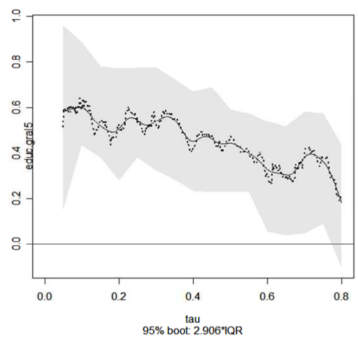
Incomplete Secondary



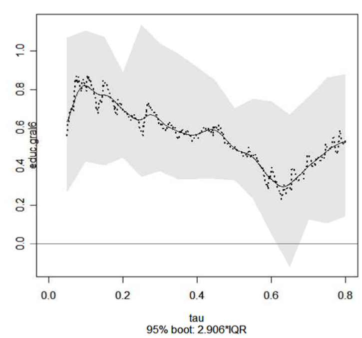
Complete Secondary



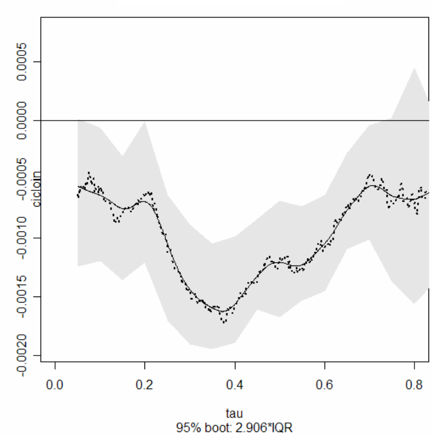
Incomplete University



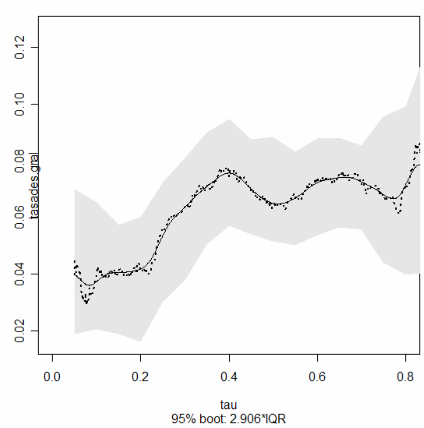
Complete University



Business Cycle



Unemployment Rate



Graph A. 5

Empirical hazard functions estimated from Quantile Regression. Unemployment hazard rate