Job Duration and the Informal Sector in Brazil

Gabriel Ulyssea
ulyssea@ipea.gov.br

Dimitri Szerman
dimitrijoe@ipea.gov.br

Instituto de Pesquisa econômica Aplicada
Av. Presidente Antônio Carlos, 51, 14º andar
Centro, 20020-010
Rio de Janeiro, RJ

24th July 2006

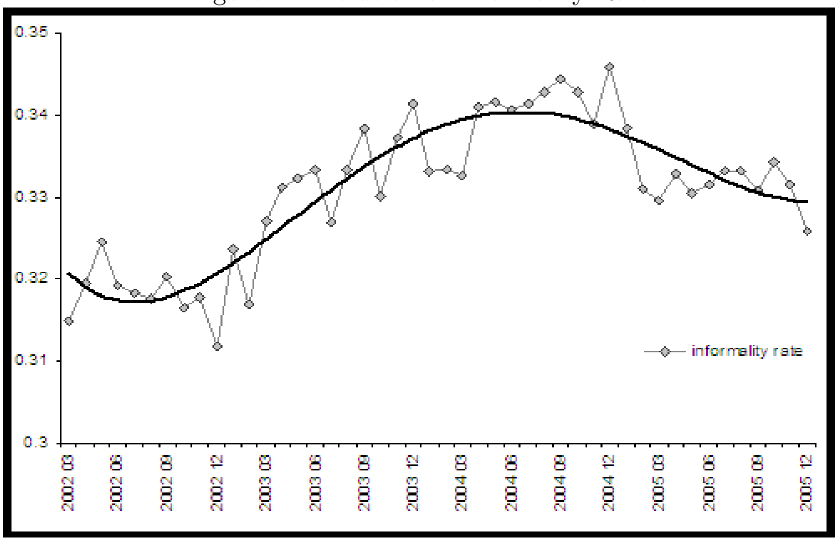
Abstract

We use data from the Monthly Employment Survey [*Pesquisa Mensal do Emprego* (PME)] to estimate the determinants of job duration in the formal and informal sectors of the Brazilian labor market. We analyze workers' mobility patterns using reduced-form duration models, which are traditionally used in unemployment analysis. The technics used involve both non-parametric and parametric tools. Our main findings are that transitions out of the formal and informal labor market are governed by different patterns. While schooling and age are positively associated with job duration in the formal sector, the opposite is true for the informal sector. Also, we find indications of the existence of an "informality trap", as the hazard rates out of informal job decline monotonically and quite rapidly over time. This suggest that if the worker does not move out of informal employment within, say, the first 3-6 months, he is likely to experience a long informal spell.

Introduction

The existence of a large informal sector is a common feature of most Latin American labor markets and Brazil does not constitute an exception. According to the Monthly Employment Survey [*Pesquisa Mensal do Emprego* (PME)], informal employment share has fluctuated between 30% and 35% from 2002 to 2005, exhibiting an inverted-U shape behavior and an slight increasing tendency over the period (Figure 1).[1] Moreover, despite the fact that gross wage differentials between formal and informal workers have been falling over the last ten years, they remain in extremely high levels (above 80%). Even after controlling for several observable characteristics, these wage differentials remain high and, more worrisome, have been increasing in the past ten years, showing an opposite behavior to the gross wage gap (Figure 2).

Figure 1: Evolution of Informality Rate

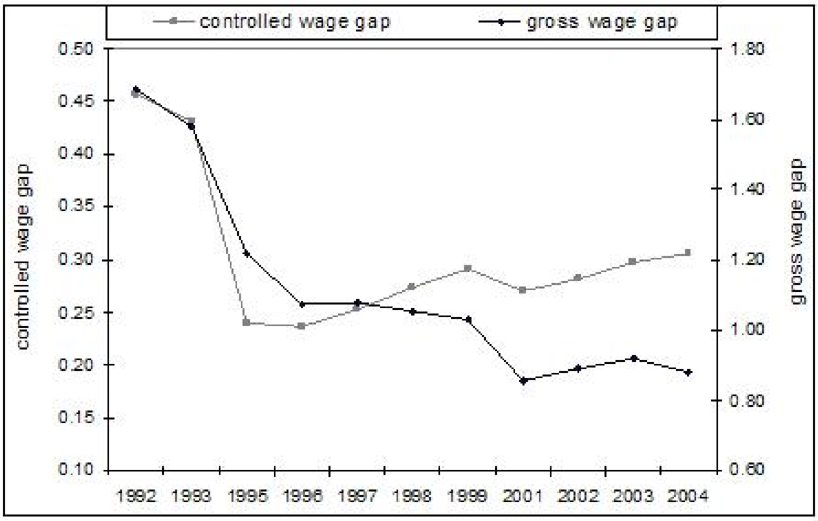


These evidences have long motivated an intense debate on whether or not Brazilian labor market is segmented and the possible welfare consequences of such segmentation.[2] In particular, formal-informal wage gap has been one of the most investigated aspects in informality literature in Brazil [Ulyssea (2006)]. This association between labor market segmentation and wage differentials is based on the assumption that formal jobs are subject to a non-price rationing and that there are barriers of entry into the formal sector (due, for instance, to the existence of unions or very restrictive labor market regulations). In this context, completely homogeneous workers – both in terms of productivity and preferences – could receive different wages depending on what sector they are allocated.

[1] Informal employment shares are calculated as the ratio between informal salaried workers (*sem carteira*) and total salaried workers (more on the definition of formal and informal sectors in Section 1)

[2] In fact, Dickens and Lang (1988) point out that, after being somewhat popular in late 1960's early 1970's, segmented labor market theory started to receive increased attention from mid-1980's.

Figure 2: Evolution of Informality Rate



Source: Authors' calculations from the National Household Survey (PNAD).
Note: the regression includes the following controls: age, age square, education, education square, dummy for household head, regional controls, sector, gender, race and firm size.

On the other hand, several authors argue that the solely observation of wage differentials is an important, though not sufficient indication of segmentation. Maloney (1999) argues that the analysis of wage differentials and the mechanisms of wage determination across sectors is not an adequate approach to analyze formal-informal labor market segmentation. In order to assess the existence of segmentation, one must investigate workers' mobility pattern between sectors. If formal sector jobs are truly preferred to informal ones, then both informal and unemployed workers will queue up for formal jobs [Dickens and Lang (1992)]. Analyzing the mobility pattern of Mexican workers through transition matrices and multinomial logit estimates, Maloney (1999) finds some results that contradict segmentation hypothesis. Similarly, Gong et al. (2004) estimate a dynamic multinomial logit panel data model with random effects to analyze workers' mobility between formal and informal employment and non-employment status in Mexico. Among other results, these authors point that for the less educated workers there seems to be some significant barriers of entry into the formal sector.

Until recently, the analysis of labor market segmentation in Brazil was mainly focused at the analysis of wage differentials and the process of wage determination in both sectors. Carneiro and Henley (2001) and Menezes-Filho et al. (2004) find that selection bias has an important role in the the determination of the wage gap, therefore favoring the competitive markets hypothesis. Oppositely, Tannuri-Pianto and Pianto (2002) and Soares (2004) find some evidences that favor the view of formal-informal labor market segmentation. In the first, the authors find some evidence that the labor market is partially segmented, as workers located at the bottom of the earnings distribution face a segmented labor market while those at the upper tail don't. In the second, Soares

(2004) also analyzes labor market segmentation trough the lens of wage determination and wage differentials literature (he estimates a endogenous switching model). However, he employs a job queue approach and, therefore, his work is also related to the job mobility literature.

An important early exception in the literature relative to labor market segmentation in Brazil is the work of Barros et al. (1990), which investigates the mobility of formal and informal employees in the metropolitan region of São Paulo.[3] These authors find high mobility rates between both sectors, estimating that nearly 50% of informal workers in any given year will be employed in formal jobs in the following year. Therefore, they conclude that the consequences of informality are only relevant in the short term and don't have any great impact on long term wage distribution. More recently, Curi and Menezes-Filho (2006) have carefully characterized labor market evolution in the 1980's and 1990's and analyzed the determinants of employment transition in Brazil. Moreover, these authors investigate average conditional wage changes associated to labor market transitions, exploiting the panel structure of the PME. They find that transitions from formality to informality and the other way around are associated to small wage decreases and increases, respectively (around 7%). Therefore, they conclude that there is some labor market segmentation in Brazil, but due to its reduce magnitude, it is likely to have minor effects on wage distribution and workers' welfare.

The objective of this paper is twofold. First, we aim to contribute to the characterization of Brazilian labor market, by providing some stylized facts relative to formal and informal employment spells, exit rates to other states and how these vary over time (duration dependence). By doing that, we also tackle a fundamental component of informality rate, namely, the duration of informality. The idea here is that, analogously to unemployment analysis, for any given flow of entry into the informal sector (let us name it the incidence rate), the higher informality duration the higher the observed informality rate. Second, and perhaps more importantly, we aim to contribute to the debate on the existence and possible consequences of formal-informal labor market segmentation in Brazil.

We analyze workers' mobility patterns through duration models, which are traditionally used in unemployment analysis.[4] We estimate reduced-form equations trying to identify the determinants of job duration. Given our objectives, special attention is given to differences between formal and informal job sectors. Although there is a growing literature in employment duration analysis [see, for instance, Lindeboom and Theeuwes (1991) and Christofides and McKenna (1996)], there is no piece of literature on employment duration in Brazil using such methods[5].

We find significantly different patterns for transitions out of the formal and informal sectors. While schooling and age are positively associated with job duration in the formal sector, the opposite is true for the informal sector. This

[3] Is worth mentioning the work of Ancora et al. (1997), which doesn't directly address the issue of labor market segmentation, but also analyzes workers mobility in both sectors.

[4] For a comprehensive survey of duration models and some applications to unemployment duration analysis, see Van den Berg (2001). For an unemployment duration analysis in Brazil, see Menezes-Filho and Picchetti (2000).

[5] There is, however, a related literature in job turnover in Brazil (for a survey, see Gonzaga (2003)). These works encompass job duration but do not take into account censoring and related features of duration data.

reinforces the view that informal jobs are of inferior quality, because the more able workers, with a broader menu of job options, are choosing formal jobs. Our findings also point to the existence of an "informality trap", as the hazard rates out of informal job decline monotonically and quite rapidly over time. This suggest that if the worker does not move out of informal employment within, say, the first 3-6 months, he is likely to experience a long informal spell. Moreover, once we disentangle the risks out of informal and informal sectors, we find that informal-formal transitions are substantially less likely to happen than the other way around.

The remaining of the paper is organized as follows. Section 1 provides information on our dataset. In Section 2 we explore data using non-parametric tools. In Section 3 we present out empirical models and discuss estimation results. Finally, Section 4 we make a more broad discussion of our results and outline further extensions of this work.

1 Data description

This paper uses panel data from the *Pesquisa Mensal de Emprego* (PME) for the period from March 2002 to December 2005[6]. In 2002 the PME went through major changes, among which was the inclusion in the survey questionnaire of retrospective questions about job duration. It is often argued that retrospective questions are likely to be contaminated with recall errors, specially for events that happened a long time in the past. We present a detailed discussion about the quality of this information in the Appendix.

To construct our sample, we use information from the first four interviews of each individual[7]. We select only individuals who report to be employed in the private sector in at least one interview[8]. This means, for example, that an individual in self-employment during the first two interviews and unemployed in the last two interviews is excluded from the sample. To avoid inconsistencies in the job duration measure, we exclude individuals holding more than one job. Also, we restrict the sample to individuals aged 15 to 65 years old in the four interviews. Details on the effects of selection rules on sample size and sample composition are presented in the Appendix.

Throughout the paper, we consider only one job spell per individual. That is, if an individual changes jobs, we ignore the spell of the second job. There is a caveat in our definition of a job spell. The PME does not ask respondents if their current job is the same as the job they held in the preceding interview. What is actually observed is the individual's job duration and occupational status. Therefore, in analyzing transitions, we take the occupational status as an individual's job. As a result, job changes within the same occupational status are ignored in the sense that they are not regarded as transitions. This caveat

[6]The PME is a monthly household survey conducted by the *Instituto Brasileiro de Geografia e Estatística* (IBGE). It is representative of the six major metropolitan areas in Brazil, namely Belo Horizonte, Porto Alegre, Recife, Rio de Janeiro, Salvador and São Paulo. The survey structure is similar to that of the US Current Population Surveys (CPS): selected households are interviewed once a month for four months, leave the sample and return eight months later for another four months of interviews.

[7]That we do not use information from all the eight interviews is due to problems with matching the individuals across the fourth and fifth interviews.

[8]Domestic work was not considered to be in the private sector.

is likely to introduce a positive bias in job duration figures presented in this paper.

Table 1 shows descriptive statistics for the sample. The two possible initial occupational status are formal and informal[9]. Formal workers are those whose job is regulated by a formal labor contract (*carteira assinada*), and informal workers do not posses this sort of contract. One third of the sample consists of informal workers. Moreover, the last line of Table 1 shows that nearly two thirds of the job spells are right-censored.

Table 2 shows the patterns of transitions between the initial state (informal or formal job) and the various possible destinations. The destinations are broadly divided into "employment" (including self-employment) and "non-employment". Note that any transition within the same occupational status is regarded as right-censored so the cells informal-informal and formal-formal give the same numbers as the appropriate cells in the last line of Table 1. We can see that transitions informal-formal are much more likely than formal-informal transitions. These figures alone could suggest absence of market segmentation (Maloney (1999)). However, as outlined in Table 1, formal and informal workers are quite different in their characteristics, and so a more careful analysis is called for.

[9]Therefore any informal-informal or formal-formal movement is treated as right censored.

Table 1: Descriptive Statistics

Variables	**Complete Sample**		**Formal**		**Informal**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Job Duration (months)	46.51	68.39	57.90	73.15	22.97	49.62
Age (years)	33.82	11.46	34.70	10.84	31.99	12.45
Male (=1 if male, 0 otherwise)	0.62	0.49	0.62	0.49	0.62	0.49
White (=1 if family head, 0 white)	0.54	0.50	0.55	0.50	0.51	0.50
Married(=1 if married, 0 otherwise)	0.64	0.48	0.68	0.47	0.55	0.50
Family Head (=1 if family head, 0 otherwise)	0.45	0.50	0.49	0.50	0.38	0.49
Schooling (years of schooling completed)	9.26	5.98	9.54	5.62	8.66	6.62
Small Firm (=1 if # Empl $\leq$ 4, 0 otherwise)	0.18	0.38	0.07	0.26	0.38	0.49
Medium Firm (=1 if 5 $\leq$ #Empl. $\leq$ 10, 0 otherwise)	0.08	0.28	0.07	0.26	0.11	0.31
Big Firm (=1 if 11 $\leq$ #Empl., 0 otherwise)	0.74	0.44	0.86	0.35	0.51	0.50
Manufacturing	0.23	0.42	0.25	0.43	0.18	0.38
Building	0.08	0.27	0.05	0.22	0.13	0.34
Comerce	0.21	0.41	0.20	0.40	0.24	0.43
Financial	0.17	0.37	0.18	0.39	0.13	0.34
Public	0.12	0.32	0.14	0.34	0.08	0.27
Service	0.19	0.39	0.18	0.38	0.23	0.42
Other	0.01	0.09	0.00	0.07	0.02	0.12
Informal (=1 if informal, 0 otherwise)	0.33	0.47				
Censored (=1 if censored, 0 otherwise)	0.67		0.77		0.44	

Notes: Sampling weights are not used.
Source: Authors' calculations from the PME.

Table 2: Transitions

Origin	Destination								
	Employment				**Employer**	**Self-Employed**	**Non-Employment**		Total
	Informal	Formal	Public	Other[a]			Unemployement	Out of the force	
	Panel A: Frequencies								
Informal	15895	5826	238	1601	782	5164	2474	4071	36051
Formal	4356	57675	3303	1637	480	1602	1654	3775	74482
Total	20251	63501	3541	3238	1262	6766	4128	7846	110533
	Panel B: Proportions								
Informal	44.1	16.2	0.7	4.4	2.2	14.3	6.9	11.3	100
Formal	5.8	77.4	4.4	2.2	0.6	2.2	2.2	5.1	100
	Panel C: Mean Spell by Transition								
Informal	22.09	25.41	39.28	20.47	39.83	33.50	9.51	14.51	-
Formal	38.23	61.16	83.13	35.47	56.04	42.66	24.13	39.94	-

[a] Includes domestic service, non-paid work and work in the public sector without a formal labor contract.
Source: Authors' calculations from the PME.

2 Nonparametric Analysis of Job Duration

Nonparametric methods impose minimal assumptions to the data, which makes their use a natural start point for any duration study. The analysis here is essentially exploratory, in the sense that it is not meant to establish causal relationships nor to quantify the effects of one variable on other variables.

One can analyze the distribution of a random variable from many perspectives. For instance, both the density function and the cumulative distribution function give full descriptions of a random variable. The choice of which function to use depends on the feature of the distribution which is to me modelled. Economists are often interested in duration dependence. As a result, the hazard function is typically used by the economic literature in duration analysis, specially in parametric models. In nonparametric analysis, however, plots of the empirical hazard function are difficult to interpret as they lack smoothness. Plots of the integrated hazard are more convenient, and so are plots of the survivor function for their direct interpretation. This section uses both of this functions to give a description of the data.

To obtain nonparametric estimates of the survivor and cumulative hazard functions, we use product-limit estimators[10]. Plots of these fuctions for formal and informal sectors are presented in Figures 3a and 3b. As can be seen, sharp contrasts are revealed. While the survivor function for jobs in the informal sector has a convex shape, the plot for formal jobs seems to be linear in duration. In turn, plots of the cumulative hazard display a concave shape for informal jobs, and is linear for formal jobs. This is an indication (see Kiefer (1988)) of negative duration dependence in the first case, and no duration dependence at all in the latter. Second, there is a considerable distance between the curves. For instance, the probability of surviving in a formal job after 100 months is nearly 75%, while the survivor probability for the informal counterpart is only 25%. This reflects the differences between average duration for formal and informal jobs, which is line with the common view that formal lasts for longer.

Since this analysis is not controlling for any variables possibly correlated with job sector, it could be that the informal-formal differences are due to other factors. For example, since it is natural to expect that firm size is negatively correlated with job informality, it could be that the above mentioned differences are due to firm size. In fact, Figure 6a (see the Appendix) shows that, for any duration, jobs in small firms have less probability of surviving than jobs in bigger firms. However, we make separate plots in an attempt to control for job sector – shown Figures 6b and 6c, also in the Appendix –, and note that the differences depicted in Figure 6a practically vanish. The same is true for other job characteristics and for demographic variables. Other selected plots are shown in the Appendix[11].

[10] These are the Kaplan-Meier and Nelson-Aalen estimators for the survivor and cumulative hazard, respectively. See, for example, Kiefer (1988).

[11] Plots controlling for firm sector, geographic region, sex, cohort, schooling, race, and status in the household are available from the authors on request.

Figure 3a: Survivor Function by Job Sector

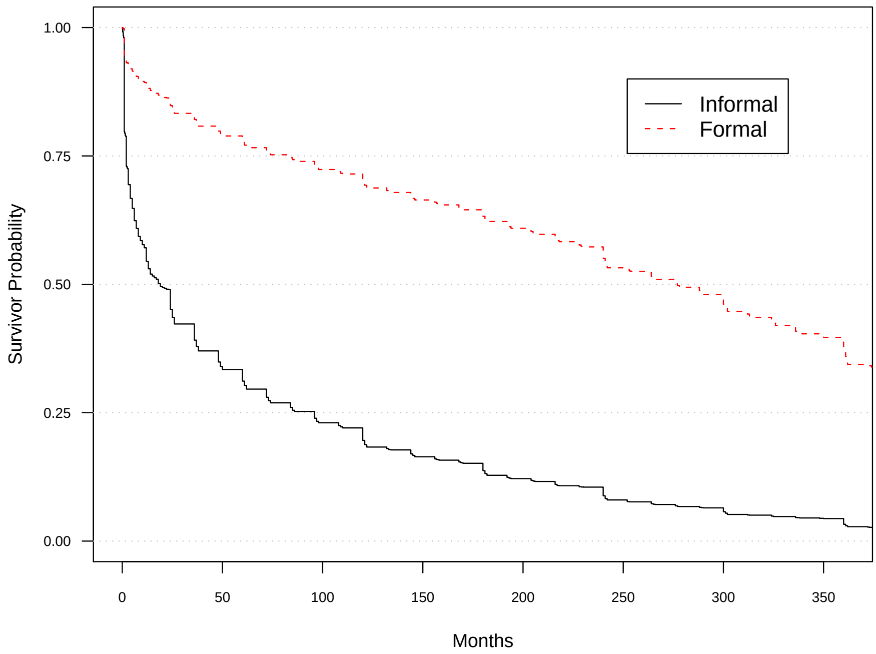
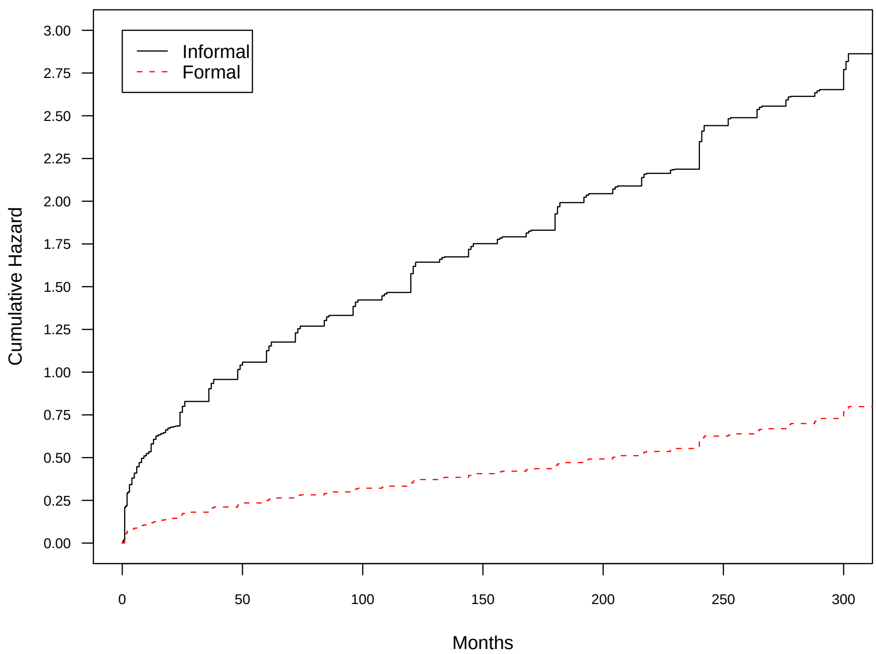


Figure 3b: Cumulative Hazard by Job Sector



3 Parametric Analysis of Job Duration

3.1 Methods

In contrast with the previous methods, parametric analysis has more predictive power at the cost of imposing more assumptions to the data. Job duration is treated as a continuous non-negative random variable denoted by T. The first assumption regards the distribution of T, and this paper uses the log-logistic distribution for that[12]. The log-logistic distribution is attractive for it is flexible enough to allow for both positive and negative duration dependence[13].

In parametric duration analysis we should be clear about the evolution of the covariates over time. In the simplest setting, it is assumed that regressors are time-invariant or, if they vary, that this variation is deterministic, as with age. Alternatively, covariates might be allowed to vary in time but, in that case, we must be able to observe enough of this variation along the spell. With a panel spanning only four months – a short time period when compared to a typical job spell – we are unable to capture this variation and therefore the analysis of time-varying covariates is ruled out.

Next, to introduce (the time-invariant) covariates in the analysis we assume that the shape parameter of the distribution of T is an exponential function of observable variables[14]. That is, we assume that $T \sim G(\alpha, \exp(\mathbf{x}'\beta))$, where $G(\cdot)$ is the log-logistic cdf, $\mathbf{x}$ is a vector of k explanatory variables and β is the associated parameter vector. The resulting hazard is

$$\lambda(t, \mathbf{x}; \alpha, \beta) = \exp(\mathbf{x}'\beta)\alpha t^{\alpha-1}/[1 + \exp(\mathbf{x}'\beta)t^{\alpha}] \ . \tag{1}$$

The loglogistic has negative duration dependence when $\alpha \leq 1$, while for $\alpha > 1$ the hazard increases until $t = [(\alpha - 1)/\gamma]^{1-\alpha}$ and decreases after that. Note that the loglogistic does not have a proportional hazard representation, and so the magnitudes of the β's have not a straightforward interpretation. Estimation is carried by maximum likelihood, taking into account right-censoring[15].

One pitfall of duration parametric models is their sensitivity to misspecification. To overcome the possibility of getting inconsistent parameter estimates due to misspecification, there is a widely used semi-parametric method that requires less distributional assumptions. That is the Cox model, which uses a proportional hazard specification with a flexible baseline hazard. The estimation is done by applying partial likelihood (see Cox (1972, 1975)) to

$$\lambda(t|\mathbf{x}, \gamma) = \lambda_0(t) \exp(\mathbf{x}'\gamma). \tag{2}$$

Equation 2 says that an unit increase in x_k multiplies $\lambda_0(t)$ – the baseline hazard – by $\exp(\gamma_k)$, and therefore implies an increase of $\exp(\gamma_k) - 1$ in the baseline. The baseline hazard is non-parametrically estimated. The cost of such flexibility is a lesser predictive power than that of parametric models, but still higher than what is achieved by non parametric methods.

---

[12] The parametrization here is the same used by Kiefer (1988).

[13] Other distributions were also used, and we discuss this point when commenting the robustness of our results.

[14] One advantage in assuming an exponential function is to assure positiveness of the parameters.

[15] Actually, statistical softwares estimate the accelerated failure time representation of the loglogistic, which models the mean of (log) T instead of the hazard.

Up to here we have ignored the fact that there are various possible destinations to an individual who leaves her job. This is an implicit assumption of a single risk hazard rate. As Table 2 shows, this might be unrealistic, as the probabilities of exit vary considerably across destinations. To relax this, we consider a competing independent risks model[16]. This enables us to look with more detail to each possible transition described in Table 2. Of particular interest to this paper are the formal-informal and informal-formal transitions.

3.2 Results

We first present and discuss results for single risk models. Table 3 shows results for both the full parametric log-logistic model and the semi-parametric Cox model. For the Cox model, we report the hazard ratios, i.e., $\exp(\gamma_k)$ (see equation 2), so $\exp(\gamma_k) > 1$ implies positive impacts on the hazard (and therefore a negative impact on expected duration). For the log-logistic model, estimates' signs are as usual: a positive β_k implies positive impact on the hazard. Therefore, whenever a coefficient from the log-logistic model is greater than zero, we should expect $\exp(\gamma_k) > 1$ in the Cox model.

Overall, at least two patterns can be identified in Table 3. First, the determinants of formal jobs' duration are somewhat different from those of informal jobs'. For personal characteristics, only the dummies for sex and race have similar signs and significance. Schooling and age are either not significant for informal workers, or have opposite signs. If more qualified and experienced workers are those who have more bargain power (or more employment options), then these results indicate that formal jobs are preferred to informal ones. These come from the fact that we observe opposite signs for schooling coefficients in both sectors, indicating that more qualified workers experience shorter informal spells, while the contrary is true for non-qualified. As for firm characteristics, firm size decreases the hazard rate of both formal and informal job, but is much more important for formal jobs. This result points to the importance of the quality of the job to workers mobility: assuming that higher firms offer better jobs, the higher the job quality the lower the hazard rates out of employment. The differences in dummy sectors are not statistically significant.

Second, the Cox and log-logistic models estimates are in conformity with each other. Although there are some differences in signs between the two models for informal workers, they are not statistically significant. These results were also robust to other distributional assumptions[17]. As the Cox model is protected against misspecification, this strengths the case for the log-logistic. The accordance between the models can also be noted in Figures 4a to 4b. The survivor curves predicted by the log-logistic and Cox models are similar in shape and magnitude for the informal sector, confirming the quality of the parametric fit for this sub-sample. However, the same cannot be said about .

The log-logistic model predicts monotonically decreasing hazards for both sectors, as $\alpha < 1$.[18] This suggests a tendency to an "informality trap", as the probability of exiting an informal job highly decreases over time. If we believe that informal jobs are of inferior quality, then this result is worrisome.

---

[16] Assuming correlated risks is a major goal for future research.

[17] Results for the Weibull and exponential models are reported in Table 7 in the Appendix.

[18] As in Section 2, we do not show plots of the predicted hazard because the Cox non-parametric estimates lack smoothness and are hard to interpret.

Table 3: Single Risk Results

	Informal		Formal	
	Log-Logis.	Cox PH	Log-Logis.	Cox PH
Personal				
Age	.019	1.004	-.188	.942
	[.287]	[.544]	[.000]	[.000]
Age^2	.000	1.000	.002	1.001
	[.038]	[.019]	[.000]	[.000]
Man	-.404	.859	-.774	.755
	[.000]	[.000]	[.000]	[.000]
White	-.118	.959	-.282	.895
	[.025]	[.031]	[.000]	[.000]
Married	-.035	.998	-.324	.895
	[.624]	[.941]	[.000]	[.000]
Head	-.023	.994	-.193	.933
	[.709]	[.785]	[.008]	[.009]
Schooling	.033	1.014	-.065	.972
	[.151]	[.082]	[.021]	[.005]
Schooling^2	-.004	.999	.000	1.000
	[.016]	[.013]	[.986]	[.810]
Firm				
Medium	-.511	.862	-1.039	.712
	[.000]	[.000]	[.000]	[.000]
Large	-.129	.980	-1.707	.562
	[.014]	[.298]	[.000]	[.000]
Building	1.006	1.350	2.463	2.278
	[.000]	[.000]	[.000]	[.000]
Comerce	-.037	.995	.737	1.313
	[.626]	[.860]	[.000]	[.000]
Financial	-.004	1.052	.646	1.279
	[.964]	[.096]	[.000]	[.000]
Public	-.086	1.011	.723	1.322
	[.407]	[.782]	[.000]	[.000]
Other	.038	1.029	.780	1.347
	[.601]	[.285]	[.000]	[.000]
Other Ctrls.				
Year	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
α	.781		.649	
	[.000]		[.000]	
Obs.	22272	22272	54590	54590
ln(PLik)	-33012	–	-40058	–

Notes: p-values from robust standard errors in brackets. For the α parameter, the null is $\alpha = 1$ against a two-sided alternative. The same is true for Cox results. The log-logistic model was estimated in its AFT form, and coefficients were appropriately scaled to the hazard representation described by equation 1.
Source: Authors' calculations.

Figure 4a: Log-Logistic Predicted Survivor: Informal

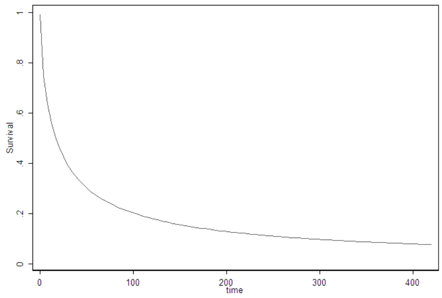


Figure 4b: Cox PH Predicted Survivor: Informal

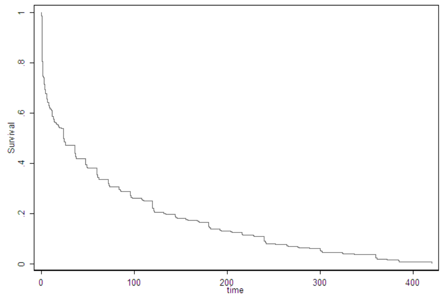


Figure 4c: Log-Logistic Predicted Survivor: Formal

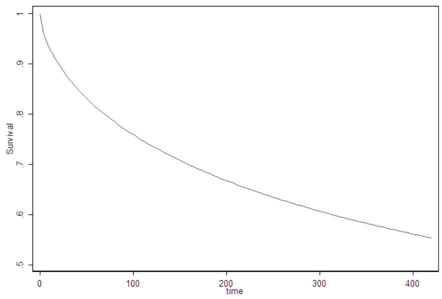
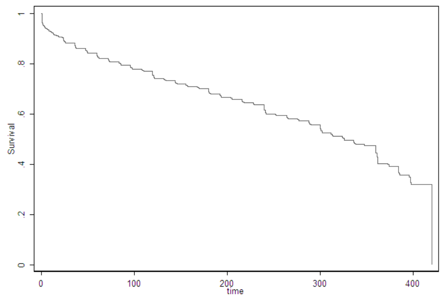


Figure 4d: Cox PH Predicted Survivor: Formal



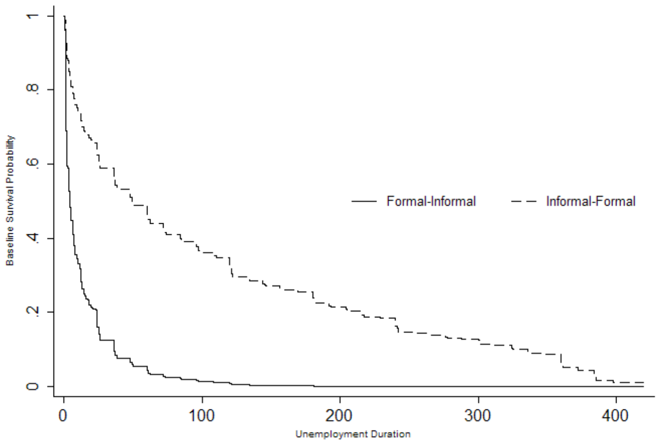
The single risk model is interesting in that it reveals different patterns for the duration of formal and informal jobs. However, if we wish to learn about what affects the transitions between this sectors, the competing risks model is more suitable. We present results for the Cox model with competing risks in Tables 4a and 4b, and leave log-logistic results to the Appendix for sake of conciseness. We focus the discussion on the results for transitions between the formal and informal sectors.

The results on personal characteristics are consistent with existing results on informality incidence.[19] The more educated the individual is, the higher her risk of making informal-formal transitions for any given duration. Using estimates from Tables 4a and 4b, an additional year of schooling increases the hazard of the informal-formal transition in 5.3%, while decreases the hazard of formal-informal transition in 1.7% (though the latter is not statistically significant). Therefore, in any given outflow of workers from the informal sector, educated workers will be over-represented and thus the average schooling of informal workers will decrease. The same is true for breadwinners, as this characteristic also decreases the risk of formal-informal transitions.

The results on firm characteristics are also as expected, but the estimates magnitude are somewhat revealing. Informal workers employed in large firms have more than the double of the chances of migrating to the formal sector in comparison with their counterparts employed in small firms. From the other

[19]There is a well established stylized fact in the informality literature that young, non-qualified, female, non-white and non-unionized workers are more likely to be informal [see, for instance, Ulyssea (2006)].

Figure 5: Competing risks Cox PH Predicted Survivor



side, chances of making the formal-informal path reduce in 45% when an individual goes from a small to a large firm. Moreover, is worth noting that the resuts indicate that firm's is the most important determinant of job duration in both sectors (though with opposite signs).

The plots of the predicted baseline survivor functions for the formal-informal and informal-formal transitions are shown in Figure 5. As we can see, for any given duration, the probability of surviving in the current state is higher for informal workers. That is, once we control for personal and job characteristics, formal-informal transitions are much more likely than the reverse.

3.2.1 Robustness

We estimate other parametric models assuming the exponential and Weibull distributions, and the results highlighted above remain largely unchanged. A major concern in duration analysis is the existence of unobserved heterogeneity. Unlike in linear models, unobserved heterogeneity biases duration models estimates even if it is uncorrelated with regressors. We follow common practice and model heterogeneity as a multiplicative error with a gamma distribution.[20] For both sectors and the log-logistic model, there was no evidence of unobserved heterogeneity as the coefficients estimates and maximized likelihood were unchanged, and the estimated heterogeneity parameter was null. When heterogeneity was added in the exponential and Weibull models, there were some changes in estimates and significant changes in the likelihood. We interpret this a sign of misspecification in these models, rather than genuine unobserved heterogeneity, because of the results for the log-logistic model. These results are reported in the Appendix. Finally, because we are not allowing regressors to vary over time, and because young individuals are likely to be engaged in education, we restricted the sample to individuals aged 24 or over. The results once again were unaffected.

[20] It is also common to assume an inverse-gaussian distribution. This will be included in future versions of this paper.

Table 4a: Cox Model with Competing Risks: Informal

	Formal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	.978	1.041	1.065	1.162	1.189	.997	.922
	[.081]	[.083]	[.000]	[.000]	[.003]	[.909]	[.000]
Age^2	1.000	.999	.999	.998	.998	1.000	1.001
	[.352]	[.002]	[.000]	[.000]	[.003]	[.745]	[.000]
Man	.957	.996	1.273	1.304	.758	.181	.525
	[.254]	[.957]	[.000]	[.004]	[.124]	[.000]	[.000]
White	.961	.777	1.046	1.402	.784	.839	.877
	[.303]	[.000]	[.204]	[.000]	[.193]	[.021]	[.014]
Married	.915	.647	1.281	1.660	.939	1.034	.805
	[.082]	[.000]	[.000]	[.000]	[.775]	[.713]	[.001]
Head	1.138	1.173	.973	1.000	1.156	.912	.718
	[.003]	[.055]	[.502]	[.997]	[.458]	[.226]	[.000]
Schooling	1.056	1.070	.999	1.092	1.025	.912	1.063
	[.001]	[.021]	[.947]	[.020]	[.739]	[.001]	[.006]
Schooling^2	.997	.994	1.000	1.002	1.004	.999	.994
	[.002]	[.002]	[.962]	[.442]	[.318]	[.690]	[.000]
Firm							
Medium	1.752	.835	.635	.887	2.503	.249	.862
	[.000]	[.073]	[.000]	[.294]	[.016]	[.000]	[.060]
Large	2.141	.849	.767	.427	5.384	.545	.863
	[.000]	[.009]	[.000]	[.000]	[.000]	[.000]	[.003]
Building	.798	1.837	1.673	1.221	1.291	1.265	1.489
	[.001]	[.000]	[.000]	[.177]	[.508]	[.223]	[.000]
Comerce	.910	.904	1.065	1.151	1.056	1.598	.879
	[.064]	[.296]	[.217]	[.234]	[.864]	[.000]	[.077]
Financial	1.041	.900	.930	.776	1.562	3.199	.900
	[.461]	[.355]	[.234]	[.076]	[.153]	[.000]	[.228]
Public	1.011	.609	.655	.664	5.478	3.779	.793
	[.873]	[.003]	[.000]	[.035]	[.000]	[.000]	[.032]
Other	.869	1.087	1.068	.946	1.442	1.902	.977
	[.005]	[.352]	[.176]	[.648]	[.197]	[.000]	[.740]
Other Ctrls.							
2003	.838	1.081	.953	1.170	1.184	.779	.848
	[.000]	[.356]	[.309]	[.191]	[.468]	[.007]	[.018]
2004	.767	.856	.926	1.007	.830	.788	.871
	[.000]	[.074]	[.106]	[.952]	[.436]	[.008]	[.043]
2005	.755	.722	.766	.809	.996	.560	.745
	[.000]	[.000]	[.000]	[.093]	[.987]	[.000]	[.000]
BA	.697	.495	.489	.681	.362	.483	.383
	[.000]	[.000]	[.000]	[.066]	[.016]	[.000]	[.000]
MG	1.317	1.028	1.147	1.463	1.457	.782	1.016
	[.000]	[.769]	[.012]	[.012]	[.186]	[.023]	[.820]
RJ	.716	.332	.574	.988	1.591	.529	.222
	[.000]	[.000]	[.000]	[.939]	[.095]	[.000]	[.000]
SP	.893	1.045	.850	1.059	.560	.658	.643
	[.058]	[.629]	[.003]	[.698]	[.066]	[.000]	[.000]
RG	1.091	.956	.988	1.225	1.334	.929	.887
	[.206]	[.693]	[.848]	[.207]	[.378]	[.545]	[.156]
Obs.	22272	22272	22272	22272	22272	22272	22272

Notes: Robust p-values errors in brackets.
Source: Authors' calculations.

Table 4b: Cox Model with Competing Risks: Formal

	Informal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	.888	.933	1.067	1.169	1.128	1.041	.877
	[.000]	[.013]	[.008]	[.000]	[.000]	[.137]	[.000]
Age^2	1.001	1.000	.999	.998	.999	.999	1.002
	[.000]	[.442]	[.011]	[.002]	[.000]	[.017]	[.000]
Man	1.054	.983	1.530	1.824	.855	.134	.538
	[.265]	[.830]	[.000]	[.000]	[.046]	[.000]	[.000]
White	.972	.907	.865	1.537	.829	.762	.841
	[.505]	[.180]	[.023]	[.001]	[.015]	[.000]	[.000]
Married	.817	.723	.931	1.084	.755	1.205	.950
	[.000]	[.001]	[.487]	[.659]	[.005]	[.065]	[.392]
Head	.879	1.054	1.149	1.014	1.067	1.201	.733
	[.014]	[.568]	[.077]	[.919]	[.444]	[.016]	[.000]
Schooling	.984	1.163	1.013	1.084	1.054	.895	1.005
	[.401]	[.000]	[.645]	[.174]	[.170]	[.001]	[.813]
Schooling^2	.999	.990	1.000	1.005	1.001	.998	.995
	[.574]	[.000]	[.964]	[.108]	[.516]	[.266]	[.000]
Firm							
Medium	.838	1.106	.847	.549	2.513	.153	1.254
	[.031]	[.535]	[.183]	[.002]	[.001]	[.000]	[.029]
Large	.563	.947	.552	.212	3.305	.162	1.133
	[.000]	[.666]	[.000]	[.000]	[.000]	[.000]	[.120]
Building	1.801	2.018	4.887	2.882	1.822	1.921	2.036
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Comerce	1.371	1.171	2.022	2.105	.799	1.285	1.108
	[.000]	[.096]	[.000]	[.000]	[.131]	[.033]	[.091]
Financial	1.168	1.120	1.495	1.070	2.572	2.136	.945
	[.010]	[.254]	[.000]	[.683]	[.000]	[.000]	[.382]
Public	1.275	.787	1.231	.915	4.484	1.689	.846
	[.001]	[.096]	[.125]	[.684]	[.000]	[.000]	[.035]
Other	1.288	1.244	1.588	.939	2.100	1.854	1.108
	[.000]	[.020]	[.000]	[.721]	[.000]	[.000]	[.083]
Other Ctrl.							
2003	.862	.890	.852	.913	.927	.791	.734
	[.008]	[.202]	[.045]	[.551]	[.408]	[.008]	[.000]
2004	.850	.828	.709	.946	.708	.685	.761
	[.003]	[.037]	[.000]	[.709]	[.000]	[.000]	[.000]
2005	.657	.507	.636	.649	.501	.566	.602
	[.000]	[.000]	[.000]	[.006]	[.000]	[.000]	[.000]
BA	.680	.783	.690	.657	.356	.408	.531
	[.000]	[.050]	[.002]	[.072]	[.000]	[.000]	[.000]
MG	.838	.758	1.313	1.079	1.037	1.071	.996
	[.009]	[.013]	[.005]	[.674]	[.737]	[.509]	[.956]
RJ	.654	.406	.535	.407	.513	.422	.394
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
SP	.887	.756	.683	.647	.529	.721	.669
	[.073]	[.011]	[.000]	[.023]	[.000]	[.004]	[.000]
RG	.905	.929	1.395	1.002	.971	.901	1.160
	[.187]	[.551]	[.002]	[.993]	[.811]	[.394]	[.053]
Obs.	54590	54590	54590	54590	54590	54590	54590

Notes: Robust p-values errors in brackets.
Source: Authors' calculations.

4 Summary and Future Developments

We estimate reduce-form equations trying to assess the impacts of personal and job characteristics on job duration. The parametric analysis revealed different patterns for transitions out of the formal and informal sectors. While schooling and age are positively associated with job duration in the formal sector, the opposite is true for the informal sector. This reinforces the view that informal jobs are of inferior quality, because the more able workers, with a broader menu of job options, are choosing formal jobs. Our findings also point to the existence of an "informality trap", as the hazard rates out of informal job decline monotonically and quite rapidly over time. This suggest that if the worker does not move out of informal employment within, say, the first 3-6 months, he is likely to experience a long informal spell. Moreover, once we disentangle the risks out of informal and informal sectors, we find that informal-formal transitions are substantially less likely to happen than the other way around.

More results can be derived from the preceding analysis, and we intend to encompass them in future versions of this paper. Of particular interest is to compute expected moments (mean and percentiles) of job duration for various population groups. For that, more flexible specifications, including interactions between covariates, shall be adopted.

References

Ancora, M., D. Coelho, M. Neri, and A. Pinto (1997). Aspectos dinâmicos do desemprego e da posição na ocupação. *Estudos Econômicos 27*(2).

Barros, R., G. Sedlacek, and S. Varanda (1990). Segmentação e mobilidade no mercado de trabalho: a carteira de trabalho em são paulo. *Pesquisa e Planejamento Econômico 20*(1).

Carneiro, F. G. and A. Henley (2001). Modelling formal versus informal employment and earnings: microeconomic evidence for brazil. Proceedings of the XXIX Brazilian Economy Association Congress.

Christofides, L. N. and C. J. McKenna (1996, April). Unemployment insurance and job duration in canada. *Journal of Labor Economics 14*(2), 286–312. available at http://ideas.repec.org/a/ucp/jlabec/v14y1996i2p286-312.html.

Cox, D. (1972). Regression models and life tables. *Journal of the Royal Statistical Society B 34*, 187–220.

Cox, D. (1975). Regression models and life tables. *Biometrika 62*(2), 269–76.

Curi, A. and N. Menezes-Filho (2006). O mercado de trabalho brasileiro é segmentado? alterações no perfil da informalidade e nos diferenciais de salários nas décadas de 80 e 90. *Estudos Econômicos, forthcoming*.

Dickens, W. and K. Lang (1988). The reemergence of segmented labor market theory. *The American Economic Review 78*(2), 129–134.

Dickens, W. and K. Lang (1992). Labor market segmentation theory: Reconsidering the evidence. NBER Working Paper N.4087.

Gong, X., A. van Soest, and E. Villagomez (2004). Mobility in the urban labor market: A panel data analysis for mexico. *Economic Development and Cultural Change 53*(1).

Gonzaga, G. (2003). Labor turnover and labor legislation in brazil. *Economìa 4*(1).

Kiefer, N. M. (1988). Economic duration data and hazard functions. *Journal of Economic Literature 26*(2), 646–79.

Lindeboom, M. and J. Theeuwes (1991, August). Job duration in the netherlands: The co-existence of high turnover and permanent job attachment. *Oxford Bulletin of Economics and Statistics 53*(3), 243–64.

Maloney, W. F. (1999). Does informality imply segmentation in urban labor markets? evidence from sectoral transitions in mexico. *World Bank Economic Review 13*(2).

Menezes-Filho, N., N. Mendes, and E. Almeida (2004). O diferencial de salários formal-informal no brasil: Segmentação ou viés de seleção? *Revista Brasileira de Economia 58*(2).

Menezes-Filho, N. and Picchetti (2000). Os determinantes da duração do desemprego em São Paulo. *Pesquisa e Planejamento Econômico 30*(1).

Soares, F. (2004). Do informal workers queue for formal jobs in brazil? IPEA, Texto para Discussão N.1021.

Tannuri-Pianto, M. and D. Pianto (2002). Informal employment in brazil: A choice at the top and segmentation at the botton: a quantile regression approach. Paper presented at the Annual Meeting of the Brazilian Econometric Society.

Ulyssea, G. (2006). Informalidade no mercado de trabalho brasileiro: uma resenha da literatura. *Revista de Economia Política 26*(3).

Van den Berg, G. (2001). Duration models: Specification, identification, and multiple durations. *Handbook of Econometrics 5*, 3381–3460.

Appendix

Table 5: Sample sizes

	MG	RG	PE	RJ	SP	BA	Total
Original Sample	68082	50673	45361	66601	80826	46626	358169
Matched	65772	49175	41319	62926	76748	42100	338040
Formal or Informar	23576	18568	12127	18917	30008	12541	115737
$15 \leq$ Age ≤ 65	23225	18333	11943	18589	29581	12406	114077
Final Sample	22425	17775	11509	18007	28848	12043	110607
Year							
2002	4652	3823	2690	3344	5758	2298	22565
2003	6112	4676	3439	5145	7999	3561	30932
2004	6477	5209	3045	5367	8451	3570	32119
2005	5184	4067	2335	4151	6640	2614	24991

Table 6: Sample Composition

	Sector		Sex		Schooling						Region					
	Informal	Formal	Male	Female	$[0,3]$	$[4,7]$	8	$[9,10]$	11	+12	PE	BA	MG	RJ	SP	RG
Sector																
Informal	32.6		62.1	37.9	6.4	28.9	14.5	10.8	26.6	12.8	12.6	10.1	20.1	15.7	27.4	14.1
Formal		67.4	61.8	38.2	4.3	21.1	13.4	6.5	37.2	17.5	9.3	11.3	20.4	16.5	25.4	17.0
Sex																
Male	32.7	67.3	61.9		6.2	28.0	15.3	8.2	29.7	12.7	10.6	10.9	20.6	16.3	25.7	15.7
Female	32.4	67.6		38.1	3.1	16.5	11.2	7.4	40.5	21.3	10.0	10.8	19.7	16.2	26.7	16.7
Schooling																
$[0,3]$	41.1	58.9	75.9	24.1	5.0						13.0	10.3	20.5	15.1	24.5	16.7
$[4,7]$	39.5	60.5	73.2	26.8		23.6					10.6	8.5	22.8	15.4	23.3	19.3
8	34.1	65.9	68.8	31.2			13.8				8.4	9.3	21.4	19.3	23.9	17.9
$[9,10]$	44.1	55.9	63.8	36.2				7.9			10.4	12.3	20.4	14.6	26.0	16.3
11	25.4	74.6	54.1	45.9					33.8		11.1	13.4	19.8	15.4	26.3	13.9
+12	26.0	74.0	48.8	51.2						16.0	8.5	10.0	16.5	18.3	32.3	14.4
Region																
PE	39.6	60.4	63.3	36.7	6.3	24.4	11.2	8.0	36.8	13.2	10.4					
BA	30.1	69.9	62.2	37.8	4.7	18.5	11.7	8.9	41.5	14.6		10.9				
MG	32.3	67.7	63.0	37.0	5.0	26.5	14.5	7.9	33.0	13.0			20.3			
RJ	31.6	68.4	62.1	37.9	4.6	22.2	16.3	7.0	31.9	17.9				16.3		
SP	34.3	65.7	61.1	38.9	4.7	21.1	12.6	7.9	34.1	19.8					26.1	
RG	28.7	71.3	60.5	39.5	5.2	28.2	15.2	8.0	29.2	14.3						16.1
Means																
Age	32.0	34.7	34.2	33.2	40.5	36.7	34.4	26.8	31.4	34.4	33.7	33.7	33.1	35.3	33.5	33.9
Earnings	483.0	805.0	758.0	611.0	399.0	446.0	508.0	427.0	640.0	1707.0	476.0	605.0	609.0	720.0	903.0	679.0
Spell	23.0	58.0	50.0	41.0	50.0	46.0	45.0	30.0	45.0	59.0	43.0	50.0	42.0	53.0	47.0	45.0
Median Spell	4.0	27.0	21.0	15.0	18.0	16.0	18.0	10.0	21.0	27.0	14.0	24.0	15.0	27.0	21.0	17.0
Std. Dev.																
Age	12.5	10.8	11.6	11.1	12.0	11.8	11.2	10.0	10.3	10.7	11.3	10.9	11.5	11.6	11.4	11.8
Earnings	694.0	1035.0	1054.0	745.0	252.0	317.0	381.0	343.0	579.0	1915.0	623.0	896.0	865.0	921.0	1212.0	718.0
Spell	50.0	73.0	72.0	62.0	74.0	69.0	66.0	50.0	64.0	80.0	68.0	71.0	65.0	74.0	67.0	67.0

Table 7: Additional Single Risks Results

	Informal			Formal		
	Expon.	Exp-Γ	Weib.	Expon.	Exp-Γ	Weib.
Personal						
Age	.961	1.022	.994	.897	.883	.933
	[.000]	[.113]	[.416]	[.000]	[.000]	[.000]
Age^2	1.000	1.000	1.000	1.001	1.002	1.001
	[.343]	[.041]	[.309]	[.000]	[.000]	[.000]
Man	.741	.759	.835	.718	.561	.756
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
White	.914	.946	.945	.884	.834	.899
	[.007]	[.162]	[.010]	[.000]	[.000]	[.000]
Married	.953	.975	.992	.878	.768	.897
	[.271]	[.629]	[.787]	[.000]	[.000]	[.000]
Head	1.014	.981	.997	.920	.932	.928
	[.707]	[.674]	[.889]	[.004]	[.226]	[.005]
Schooling	1.025	1.016	1.017	.971	.980	.974
	[.069]	[.356]	[.054]	[.007]	[.351]	[.009]
Schooling^2	.998	.998	.998	1.000	.999	1.000
	[.003]	[.096]	[.004]	[.636]	[.379]	[.869]
Firm						
Medium	.839	.655	.847	.703	.440	.706
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Large	.976	.883	.973	.549	.270	.556
	[.444]	[.001]	[.195]	[.000]	[.000]	[.000]
Building	1.533	2.016	1.430	2.611	5.903	2.360
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Comerce	.991	.976	.989	1.370	1.731	1.306
	[.844]	[.681]	[.716]	[.000]	[.000]	[.000]
Financial	1.104	.945	1.049	1.347	1.617	1.268
	[.049]	[.401]	[.155]	[.000]	[.000]	[.000]
Public	1.075	.885	1.009	1.326	1.754	1.303
	[.250]	[.132]	[.837]	[.000]	[.000]	[.000]
Other	1.079	1.017	1.032	1.414	1.660	1.343
	[.081]	[.761]	[.273]	[.000]	[.000]	[.000]
Other Ctrls.						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
α			.566			.601
			[.000]			[.000]
θ		2.205			6.533	
		[.000]			[.000]	
Obs.	22272	22272	22272	54590	54590	54590
ln(PLik)	-38396	-32831	-33432	-38396	-40695	-40007

Notes: p-values from robust standard errors in brackets. For the α parameter, the null is $\alpha = 1$ against a two-sided alternative.
Source: Authors' calculations.

Table 8a: Log-Logistic Model with Competing Risks: Informal

	Formal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	-.024	.034	.071	.149	.162	-.010	-.103
	[.132]	[.185]	[.000]	[.000]	[.010]	[.709]	[.000]
Age^2	.000	-.001	-.001	-.002	-.002	.000	.002
	[.231]	[.003]	[.000]	[.000]	[.013]	[.940]	[.000]
Man	-.061	-.061	.268	.279	-.302	-1.867	-.773
	[.199]	[.435]	[.000]	[.004]	[.099]	[.000]	[.000]
White	-.070	-.292	.047	.337	-.252	-.200	-.166
	[.138]	[.000]	[.289]	[.000]	[.187]	[.017]	[.007]
Married	-.121	-.483	.301	.532	-.078	.022	-.271
	[.055]	[.000]	[.000]	[.000]	[.730]	[.825]	[.000]
Head	.168	.189	-.040	.009	.152	-.114	-.357
	[.002]	[.034]	[.435]	[.931]	[.454]	[.188]	[.000]
Schooling	.068	.081	-.007	.093	.021	-.114	.071
	[.001]	[.012]	[.697]	[.018]	[.773]	[.000]	[.005]
$Schooling^2$	-.004	-.007	.000	.002	.004	.000	-.007
	[.001]	[.001]	[.778]	[.448]	[.304]	[.939]	[.000]
Firm							
Medium	.626	-.199	-.610	-.182	.865	-1.530	-.183
	[.000]	[.071]	[.000]	[.135]	[.026]	[.000]	[.043]
Large	.906	-.176	-.367	-.938	1.702	-.653	-.175
	[.000]	[.010]	[.000]	[.000]	[.000]	[.000]	[.002]
Building	-.199	.715	.769	.326	.352	.337	.527
	[.024]	[.000]	[.000]	[.037]	[.368]	[.096]	[.000]
Comerce	-.117	-.118	.072	.125	.032	.512	-.162
	[.066]	[.262]	[.261]	[.313]	[.921]	[.000]	[.055]
Financial	.045	-.103	-.131	-.288	.399	1.238	-.133
	[.515]	[.405]	[.077]	[.055]	[.202]	[.000]	[.181]
Public	.004	-.509	-.502	-.449	1.690	1.444	-.254
	[.957]	[.004]	[.000]	[.026]	[.000]	[.000]	[.041]
Other	-.171	.092	.059	-.027	.357	.722	-.016
	[.006]	[.353]	[.334]	[.834]	[.216]	[.000]	[.842]
Other Ctrls.							
2003	-.207	.075	-.076	.138	.170	-.260	-.213
	[.001]	[.424]	[.204]	[.282]	[.484]	[.014]	[.009]
2004	-.315	-.172	-.105	-.005	-.224	-.271	-.186
	[.000]	[.073]	[.075]	[.967]	[.362]	[.008]	[.019]
2005	-.342	-.358	-.359	-.250	-.045	-.640	-.358
	[.000]	[.000]	[.000]	[.061]	[.855]	[.000]	[.000]
BA	-.468	-.796	-.952	-.468	-1.128	-.899	-1.098
	[.000]	[.000]	[.000]	[.030]	[.011]	[.000]	[.000]
MG	.362	.059	.160	.429	.407	-.252	.037
	[.000]	[.579]	[.022]	[.007]	[.170]	[.043]	[.656]
RJ	-.411	-1.205	-.775	-.081	.412	-.815	-1.699
	[.000]	[.000]	[.000]	[.620]	[.155]	[.000]	[.000]
SP	-.146	.056	-.270	.030	-.668	-.518	-.502
	[.049]	[.588]	[.000]	[.845]	[.041]	[.000]	[.000]
RG	.137	-.057	-.071	.215	.242	-.134	-.129
	[.114]	[.652]	[.367]	[.205]	[.468]	[.325]	[.192]
Constant	-2.933	-3.370	-4.552	-9.490	-11.848	-1.996	-.559
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.157]
α	.739	.501	.647	.572	.550	.569	.553
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.157]
Obs.	22272	22272	22272	22272	22272	22272	22272
ln(PLik)	-44333						

Notes: Robust p-values in brackets.
Source: Authors' calculations.

Table 8b: Log-Logistic Model with Competing Risks: Formal

	Informal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	-.138	-.085	.053	.155	.113	.035	-.147
	[.000]	[.002]	[.031]	[.000]	[.000]	[.229]	[.000]
Age^2	.001	.001	-.001	-.002	-.001	-.001	.002
	[.000]	[.223]	[.060]	[.003]	[.002]	[.053]	[.000]
Man	.047	-.029	.428	.618	-.134	-2.112	-.652
	[.335]	[.717]	[.000]	[.000]	[.095]	[.000]	[.000]
White	-.028	-.100	-.147	.447	-.161	-.275	-.181
	[.530]	[.174]	[.025]	[.001]	[.040]	[.000]	[.000]
Married	-.217	-.334	-.069	.091	-.289	.175	-.053
	[.000]	[.001]	[.513]	[.622]	[.005]	[.107]	[.402]
Head	-.139	.048	.138	.012	.060	.204	-.335
	[.011]	[.613]	[.086]	[.934]	[.494]	[.013]	[.000]
Schooling	-.015	.154	.019	.089	.069	-.127	.005
	[.468]	[.000]	[.509]	[.143]	[.078]	[.000]	[.816]
$Schooling^2$	-.001	-.011	.000	.005	.001	-.002	-.006
	[.498]	[.000]	[.953]	[.116]	[.564]	[.463]	[.000]
Firm							
Medium	-.192	.094	-.186	-.638	.950	-2.056	.218
	[.028]	[.569]	[.152]	[.001]	[.001]	[.000]	[.047]
Large	-.610	-.066	-.636	-1.619	1.214	-1.990	.111
	[.000]	[.613]	[.000]	[.000]	[.000]	[.000]	[.192]
Building	.655	.762	1.701	1.145	.661	.708	.796
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Comerce	.325	.169	.722	.738	-.257	.249	.106
	[.000]	[.080]	[.000]	[.000]	[.083]	[.044]	[.096]
Financial	.158	.130	.409	.048	.937	.776	-.064
	[.011]	[.198]	[.000]	[.773]	[.000]	[.000]	[.342]
Public	.242	-.242	.199	-.112	1.511	.542	-.180
	[.002]	[.097]	[.147]	[.608]	[.000]	[.000]	[.032]
Other	.261	.233	.473	-.062	.733	.666	.109
	[.000]	[.015]	[.000]	[.730]	[.000]	[.000]	[.076]
Other Ctrl.							
2003	-.153	-.119	-.162	-.087	-.084	-.254	-.327
	[.010]	[.201]	[.050]	[.576]	[.372]	[.008]	[.000]
2004	-.172	-.193	-.359	-.082	-.375	-.407	-.295
	[.003]	[.037]	[.000]	[.588]	[.000]	[.000]	[.000]
2005	-.442	-.693	-.479	-.458	-.741	-.609	-.542
	[.000]	[.000]	[.000]	[.005]	[.000]	[.000]	[.000]
BA	-.407	-.241	-.399	-.419	-1.037	-.943	-.667
	[.000]	[.059]	[.001]	[.077]	[.000]	[.000]	[.000]
MG	-.190	-.280	.276	.113	.037	.069	-.009
	[.008]	[.014]	[.006]	[.535]	[.737]	[.541]	[.899]
RJ	-.449	-.913	-.669	-.904	-.680	-.942	-.982
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
SP	-.140	-.286	-.413	-.446	-.691	-.380	-.439
	[.048]	[.011]	[.000]	[.022]	[.000]	[.002]	[.000]
RG	-.105	-.064	.332	.004	-.043	-.114	.149
	[.184]	[.609]	[.003]	[.985]	[.739]	[.392]	[.066]
Constant	-1.256	-3.262	-6.848	-11.188	-10.976	-2.642	-1.174
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
α	.688	.572	.515	.522	.681	.569	.633
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Obs.	54590	54590	54590	54590	54590	54590	54590
ln(PLik)	-56387						

Notes: Robust p-values errors in brackets.
Source: Authors' calculations.

Table 9a: Weibull Model with Competing Risks: Informal

	Formal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	.966	1.031	1.057	1.153	1.169	.989	.914
	[0.008]	[0.203]	[0.000]	[0.000]	[0.007]	[0.650]	[0.000]
Age^2	1.000	.999	.999	.998	.998	1.000	1.001
	[0.865]	[0.004]	[0.000]	[0.000]	[0.010]	[0.930]	[0.000]
Man	.936	.943	1.243	1.288	.752	.173	.505
	[0.095]	[0.430]	[0.000]	[0.006]	[0.117]	[0.000]	[0.000]
White	.953	.759	1.028	1.377	.795	.833	.865
	[0.224]	[0.000]	[0.451]	[0.000]	[0.215]	[0.020]	[0.009]
Married	.902	.638	1.279	1.678	.924	1.049	.802
	[0.051]	[0.000]	[0.000]	[0.000]	[0.719]	[0.609]	[0.001]
Head	1.142	1.186	.975	.997	1.169	.903	.718
	[0.004]	[0.044]	[0.540]	[0.975]	[0.427]	[0.192]	[0.000]
Schooling	1.058	1.077	1.004	1.096	1.030	.913	1.066
	[0.001]	[0.013]	[0.812]	[0.015]	[0.681]	[0.002]	[0.005]
Schooling^2	.997	.994	1.000	1.001	1.003	.999	.993
	[0.001]	[0.001]	[0.643]	[0.530]	[0.387]	[0.556]	[0.000]
Firm							
Medium	1.747	.828	.617	.854	2.387	.241	.849
	[0.000]	[0.066]	[0.000]	[0.168]	[0.023]	[0.000]	[0.045]
Large	2.151	.847	.752	.414	5.348	.545	.856
	[0.000]	[0.010]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]
Building	.808	1.947	1.814	1.340	1.399	1.394	1.593
	[0.003]	[0.000]	[0.000]	[0.049]	[0.385]	[0.090]	[0.000]
Comerce	.906	.896	1.052	1.137	1.028	1.629	.880
	[0.058]	[0.266]	[0.331]	[0.276]	[0.930]	[0.000]	[0.093]
Financial	1.044	.912	.921	.771	1.505	3.196	.907
	[0.448]	[0.430]	[0.186]	[0.069]	[0.190]	[0.000]	[0.280]
Public	1.021	.620	.648	.653	5.246	3.811	.796
	[0.768]	[0.005]	[0.000]	[0.028]	[0.000]	[0.000]	[0.041]
Other	.873	1.102	1.065	.947	1.418	1.951	.986
	[0.008]	[0.292]	[0.207]	[0.656]	[0.221]	[0.000]	[0.845]
Other Ctrls.							
2003	.835	1.069	.945	1.158	1.207	.792	.846
	[0.000]	[0.443]	[0.249]	[0.224]	[0.420]	[0.016]	[0.022]
2004	.762	.847	.916	1.007	.822	.784	.867
	[0.000]	[0.064]	[0.072]	[0.957]	[0.412]	[0.009]	[0.043]
2005	.757	.716	.753	.799	.970	.553	.742
	[0.000]	[0.000]	[0.000]	[0.077]	[0.897]	[0.000]	[0.000]
BA	.695	.479	.460	.629	.331	.447	.367
	[0.000]	[0.000]	[0.000]	[0.027]	[0.009]	[0.000]	[0.000]
MG	1.330	1.055	1.162	1.481	1.468	.802	1.039
	[0.000]	[0.583]	[0.008]	[0.009]	[0.182]	[0.051]	[0.608]
RJ	.713	.323	.541	.924	1.480	.498	.214
	[0.000]	[0.000]	[0.000]	[0.609]	[0.160]	[0.000]	[0.000]
SP	.899	1.059	.829	1.028	.524	.646	.640
	[0.083]	[0.545]	[0.001]	[0.853]	[0.041]	[0.000]	[0.000]
RG	1.092	.956	.975	1.206	1.294	.917	.880
	[0.213]	[0.700]	[0.689]	[0.245]	[0.431]	[0.488]	[0.145]
α	.652	.475	.569	.556	.542	.535	.509
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Obs.	22272	22272	22272	22272	22272	22272	22272
ln(PLik)	-52129						

Notes: Robust p-values errors in brackets.
Source: Authors' calculations.

Table 9b: Weibull Model with Competing Risks: Formal

	Informal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	.876	.919	1.053	1.166	1.120	1.034	.872
	[0.000]	[0.002]	[0.030]	[0.000]	[0.000]	[0.218]	[0.000]
Age^2	1.001	1.000	.999	.998	.999	.999	1.002
	[0.000]	[0.223]	[0.054]	[0.002]	[0.001]	[0.043]	[0.000]
Man	1.051	.972	1.525	1.844	.881	.131	.537
	[0.292]	[0.721]	[0.000]	[0.000]	[0.103]	[0.000]	[0.000]
White	.974	.905	.864	1.547	.849	.768	.842
	[0.529]	[0.172]	[0.023]	[0.001]	[0.031]	[0.000]	[0.000]
Married	.815	.720	.933	1.093	.760	1.217	.951
	[0.000]	[0.001]	[0.498]	[0.626]	[0.006]	[0.056]	[0.405]
Head	.875	1.048	1.144	1.008	1.053	1.200	.731
	[0.011]	[0.614]	[0.087]	[0.954]	[0.541]	[0.017]	[0.000]
Schooling	.985	1.164	1.018	1.091	1.073	.891	1.006
	[0.447]	[0.000]	[0.529]	[0.144]	[0.065]	[0.000]	[0.763]
Schooling^2	.999	.989	1.000	1.005	1.001	.998	.995
	[0.530]	[0.000]	[0.941]	[0.119]	[0.655]	[0.323]	[0.000]
Firm							
Medium	.836	1.102	.836	.540	2.548	.148	1.241
	[0.030]	[0.550]	[0.154]	[0.001]	[0.001]	[0.000]	[0.038]
Large	.561	.943	.542	.207	3.312	.156	1.118
	[0.000]	[0.644]	[0.000]	[0.000]	[0.000]	[0.000]	[0.168]
Building	1.850	2.097	5.150	2.994	1.891	1.948	2.100
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Comerce	1.371	1.183	2.022	2.069	.767	1.261	1.106
	[0.000]	[0.077]	[0.000]	[0.000]	[0.073]	[0.050]	[0.096]
Financial	1.167	1.137	1.487	1.055	2.503	2.068	.942
	[0.010]	[0.197]	[0.000]	[0.746]	[0.000]	[0.000]	[0.358]
Public	1.264	.787	1.219	.900	4.286	1.623	.840
	[0.002]	[0.097]	[0.144]	[0.629]	[0.000]	[0.000]	[0.029]
Other	1.291	1.259	1.587	.937	2.058	1.820	1.108
	[0.000]	[0.014]	[0.000]	[0.713]	[0.000]	[0.000]	[0.084]
Other Ctrl.							
2003	.863	.888	.851	.913	.927	.797	.735
	[0.008]	[0.193]	[0.045]	[0.553]	[0.402]	[0.011]	[0.000]
2004	.849	.826	.707	.928	.697	.689	.760
	[0.003]	[0.036]	[0.000]	[0.616]	[0.000]	[0.000]	[0.000]
2005	.656	.506	.629	.638	.488	.566	.601
	[0.000]	[0.000]	[0.000]	[0.005]	[0.000]	[0.000]	[0.000]
BA	.682	.789	.679	.657	.360	.401	.530
	[0.000]	[0.059]	[0.001]	[0.072]	[0.000]	[0.000]	[0.000]
MG	.835	.760	1.310	1.097	1.031	1.052	.994
	[0.008]	[0.014]	[0.005]	[0.610]	[0.774]	[0.624]	[0.934]
RJ	.654	.407	.523	.406	.517	.414	.392
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SP	.878	.756	.668	.638	.512	.694	.662
	[0.054]	[0.011]	[0.000]	[0.019]	[0.000]	[0.001]	[0.000]
RG	.903	.936	1.380	1.003	.957	.869	1.157
	[0.176]	[0.592]	[0.003]	[0.988]	[0.726]	[0.248]	[0.058]
α	.671	.567	.508	.518	.674	.549	.615
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Obs.	54590	54590	54590	54590	54590	54590	54590
ln(PLik)	-56381						

Notes: Robust p-values errors in brackets.
Source: Authors' calculations.

Table 10a: Exponential Model with Competing Risks: Informal

	Formal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	.934	.994	1.029	1.120	1.115	.947	.882
	[.000]	[.804]	[.060]	[.001]	[.067]	[.054]	[.000]
Age^2	1.000	.999	.999	.999	.999	1.000	1.001
	[.240]	[.046]	[.001]	[.000]	[.043]	[.458]	[.000]
Man	.852	.805	1.106	1.134	.700	.151	.442
	[.000]	[.007]	[.036]	[.197]	[.059]	[.000]	[.000]
White	.928	.709	.992	1.316	.775	.837	.845
	[.105]	[.000]	[.869]	[.004]	[.187]	[.043]	[.010]
Married	.862	.621	1.226	1.566	.833	1.080	.781
	[.014]	[.000]	[.002]	[.001]	[.423]	[.488]	[.002]
Head	1.151	1.205	.996	1.043	1.157	.902	.726
	[.008]	[.044]	[.937]	[.683]	[.473]	[.246]	[.000]
Schooling	1.063	1.095	1.013	1.113	1.041	.915	1.074
	[.002]	[.007]	[.482]	[.008]	[.598]	[.012]	[.008]
Schooling^2	.996	.992	.999	1.000	1.002	.998	.993
	[.001]	[.000]	[.228]	[.994]	[.584]	[.352]	[.000]
Firm							
Medium	1.752	.808	.605	.840	2.412	.240	.839
	[.000]	[.061]	[.000]	[.150]	[.021]	[.000]	[.061]
Large	2.205	.848	.739	.410	5.375	.553	.859
	[.000]	[.023]	[.000]	[.000]	[.000]	[.000]	[.013]
Building	.828	2.233	1.958	1.450	1.404	1.558	1.777
	[.023]	[.000]	[.000]	[.018]	[.384]	[.032]	[.000]
Comerce	.904	.882	1.056	1.147	1.051	1.692	.891
	[.096]	[.241]	[.378]	[.266]	[.878]	[.000]	[.188]
Financial	1.083	.964	.975	.798	1.580	3.433	.975
	[.233]	[.773]	[.731]	[.129]	[.151]	[.000]	[.802]
Public	1.081	.666	.692	.675	5.763	4.114	.850
	[.346]	[.026]	[.000]	[.053]	[.000]	[.000]	[.209]
Other	.898	1.162	1.117	.973	1.450	2.132	1.030
	[.071]	[.136]	[.063]	[.833]	[.197]	[.000]	[.725]
Other Ctrls.							
2003	.816	1.036	.945	1.168	1.243	.780	.838
	[.001]	[.722]	[.370]	[.225]	[.375]	[.027]	[.043]
2004	.745	.826	.914	1.002	.846	.750	.854
	[.000]	[.057]	[.146]	[.987]	[.501]	[.008]	[.061]
2005	.761	.701	.759	.811	1.032	.544	.744
	[.000]	[.001]	[.000]	[.116]	[.898]	[.000]	[.001]
BA	.684	.441	.434	.590	.312	.430	.354
	[.000]	[.000]	[.000]	[.014]	[.007]	[.000]	[.000]
MG	1.388	1.130	1.223	1.513	1.467	.840	1.127
	[.000]	[.276]	[.006]	[.010]	[.204]	[.192]	[.187]
RJ	.700	.301	.520	.878	1.407	.482	.208
	[.000]	[.000]	[.000]	[.422]	[.240]	[.000]	[.000]
SP	.928	1.109	.868	1.046	.535	.660	.673
	[.291]	[.334]	[.045]	[.770]	[.056]	[.001]	[.000]
RG	1.111	.954	.970	1.193	1.353	.916	.887
	[.205]	[.719]	[.702]	[.300]	[.374]	[.544]	[.253]
Obs.	22272	22272	22272	22272	22272	22272	22272
ln(PLik)	-57193						

Notes: Robust p-values errors in brackets.
Source: Authors' calculations.

Table 10b: Exponential Model with Competing Risks: Formal

	Informal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	.848	.881	1.004	1.110	1.080	1.003	.842
	[.000]	[.000]	[.856]	[.018]	[.006]	[.923]	[.000]
Age^2	1.002	1.001	1.000	.999	.999	.999	1.002
	[.000]	[.039]	[.470]	[.024]	[.014]	[.139]	[.000]
Man	1.011	.925	1.436	1.758	.860	.118	.509
	[.824]	[.330]	[.000]	[.000]	[.056]	[.000]	[.000]
White	.962	.892	.842	1.503	.836	.754	.828
	[.379]	[.121]	[.009]	[.003]	[.020]	[.000]	[.000]
Married	.801	.705	.904	1.057	.742	1.237	.935
	[.000]	[.000]	[.333]	[.763]	[.003]	[.046]	[.274]
Head	.866	1.030	1.127	1.000	1.055	1.185	.724
	[.007]	[.755]	[.136]	[.999]	[.532]	[.036]	[.000]
Schooling	.983	1.160	1.014	1.079	1.064	.887	1.003
	[.400]	[.000]	[.639]	[.198]	[.107]	[.001]	[.892]
Schooling^2	.999	.989	.999	1.004	1.001	.997	.994
	[.384]	[.000]	[.704]	[.125]	[.672]	[.210]	[.000]
Firm							
Medium	.836	1.095	.838	.533	2.515	.144	1.240
	[.034]	[.581]	[.171]	[.001]	[.001]	[.000]	[.045]
Large	.561	.941	.535	.199	3.233	.150	1.103
	[.000]	[.638]	[.000]	[.000]	[.000]	[.000]	[.239]
Building	2.012	2.385	5.895	3.218	2.014	2.127	2.314
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Comerce	1.423	1.244	2.169	2.245	.807	1.342	1.154
	[.000]	[.023]	[.000]	[.000]	[.148]	[.016]	[.022]
Financial	1.224	1.221	1.614	1.115	2.629	2.206	1.006
	[.001]	[.049]	[.000]	[.513]	[.000]	[.000]	[.926]
Public	1.281	.800	1.268	.943	4.424	1.619	.851
	[.001]	[.128]	[.084]	[.789]	[.000]	[.000]	[.048]
Other	1.345	1.336	1.691	.991	2.133	1.948	1.161
	[.000]	[.002]	[.000]	[.959]	[.000]	[.000]	[.014]
Other Ctrl.							
2003	.854	.874	.833	.899	.927	.796	.723
	[.006]	[.148]	[.026]	[.496]	[.407]	[.017]	[.000]
2004	.842	.818	.699	.927	.701	.680	.757
	[.002]	[.030]	[.000]	[.614]	[.000]	[.000]	[.000]
2005	.652	.502	.621	.635	.491	.567	.598
	[.000]	[.000]	[.000]	[.005]	[.000]	[.000]	[.000]
BA	.703	.821	.694	.663	.363	.403	.546
	[.000]	[.121]	[.003]	[.081]	[.000]	[.000]	[.000]
MG	.857	.780	1.335	1.094	1.043	1.114	1.030
	[.027]	[.029]	[.003]	[.624]	[.698]	[.322]	[.682]
RJ	.665	.415	.524	.403	.518	.415	.402
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
SP	.895	.769	.678	.641	.518	.716	.682
	[.106]	[.019]	[.000]	[.021]	[.000]	[.005]	[.000]
RG	.930	.965	1.444	1.033	.987	.895	1.220
	[.349]	[.774]	[.001]	[.870]	[.916]	[.389]	[.012]
Obs.	54590	54590	54590	54590	54590	54590	54590
ln(PLik)	-58763						

Notes: Robust p-values errors in brackets.
Source: Authors' calculations.

Table 11a: Exponential Model with Gamma Heterogeneity and Competing Risks: Informal

	Formal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	1.019	1.076	1.119	1.195	1.441	.981	.854
	[.402]	[.125]	[.000]	[.007]	[.001]	[.673]	[.000]
Age^2	.999	.998	.999	.998	.996	1.000	1.002
	[.001]	[.011]	[.000]	[.021]	[.002]	[.830]	[.000]
Man	.926	.867	1.548	1.945	.568	.058	.318
	[.262]	[.267]	[.000]	[.000]	[.082]	[.000]	[.000]
White	.889	.680	1.124	1.947	.793	.876	.861
	[.081]	[.001]	[.098]	[.000]	[.489]	[.347]	[.135]
Married	.834	.460	1.576	2.392	.880	.957	.580
	[.040]	[.000]	[.000]	[.001]	[.760]	[.807]	[.000]
Head	1.268	1.539	.923	1.127	1.343	.819	.638
	[.003]	[.003]	[.323]	[.556]	[.430]	[.173]	[.000]
Schooling	1.093	1.131	.956	1.190	.985	.814	1.132
	[.004]	[.024]	[.120]	[.022]	[.903]	[.001]	[.003]
Schooling^2	.995	.990	1.003	1.002	1.012	1.004	.988
	[.003]	[.004]	[.097]	[.725]	[.088]	[.270]	[.000]
Firm							
Medium	2.144	.823	.372	.576	4.462	.081	.817
	[.000]	[.290]	[.000]	[.022]	[.020]	[.000]	[.189]
Large	3.330	.836	.557	.173	14.545	.391	.770
	[.000]	[.125]	[.000]	[.000]	[.000]	[.000]	[.007]
Building	.903	2.498	2.717	1.968	1.887	1.595	2.359
	[.405]	[.000]	[.000]	[.028]	[.345]	[.152]	[.000]
Comerce	.864	.778	1.186	.945	1.090	1.849	.700
	[.111]	[.148]	[.107]	[.825]	[.880]	[.008]	[.012]
Financial	1.028	.766	.709	.563	1.640	4.926	.702
	[.778]	[.207]	[.008]	[.072]	[.352]	[.000]	[.042]
Public	.924	.351	.434	.453	16.179	7.183	.663
	[.513]	[.001]	[.000]	[.053]	[.000]	[.000]	[.037]
Other	.772	1.002	1.070	.995	1.936	2.908	.979
	[.003]	[.991]	[.514]	[.984]	[.178]	[.000]	[.869]
Other Ctrls.							
2003	.767	1.043	.960	1.191	1.238	.733	.705
	[.003]	[.784]	[.670]	[.470]	[.634]	[.085]	[.007]
2004	.688	.778	.887	.928	.664	.715	.755
	[.000]	[.115]	[.197]	[.757]	[.374]	[.057]	[.026]
2005	.624	.539	.626	.584	.953	.475	.568
	[.000]	[.000]	[.000]	[.029]	[.914]	[.000]	[.000]
BA	.492	.272	.220	.553	.184	.265	.215
	[.000]	[.000]	[.000]	[.153]	[.016]	[.000]	[.000]
MG	1.666	.945	1.134	2.254	2.317	.660	1.006
	[.000]	[.726]	[.225]	[.004]	[.107]	[.041]	[.962]
RJ	.549	.117	.278	.980	2.908	.214	.064
	[.000]	[.000]	[.000]	[.946]	[.033]	[.000]	[.000]
SP	.762	1.014	.617	1.118	.307	.337	.449
	[.010]	[.929]	[.000]	[.689]	[.032]	[.000]	[.000]
RG	1.267	.858	.810	1.795	1.013	.591	.872
	[.054]	[.459]	[.084]	[.062]	[.983]	[.025]	[.393]
θ	4.095	27.032	5.984	3.657	57.874	15.306	14.090
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Obs.	22272	22272	22272	22272	22272	22272	22272
ln(PLik)	-51790						

Notes: Robust p-values errors in brackets.
Source: Authors' calculations.

Table 11b: Exponential Model with Gamma Heterogeneity and Competing Risks: Formal

	Informal	Unempl.	Self-Empl.	Employer	Public	Other	Out
Personal							
Age	.825	.909	1.157	1.316	1.085	.983	.783
	[.000]	[.102]	[.009]	[.007]	[.010]	[.732]	[.000]
Age^2	1.002	1.000	.999	.997	.999	1.000	1.003
	[.000]	[.857]	[.069]	[.035]	[.042]	[.769]	[.000]
Man	.981	.919	1.823	2.317	.837	.052	.338
	[.802]	[.594]	[.001]	[.005]	[.068]	[.000]	[.000]
White	.961	.837	.692	2.142	.842	.693	.754
	[.584]	[.250]	[.020]	[.005]	[.046]	[.004]	[.001]
Married	.681	.574	.956	1.253	.706	1.084	.806
	[.000]	[.006]	[.844]	[.548]	[.006]	[.631]	[.064]
Head	.841	1.196	1.366	1.228	1.084	1.480	.599
	[.046]	[.343]	[.099]	[.533]	[.444]	[.004]	[.000]
Schooling	.987	1.358	1.130	1.239	1.064	.850	1.004
	[.705]	[.000]	[.074]	[.096]	[.136]	[.003]	[.927]
Schooling^2	.998	.979	.998	1.006	1.001	.998	.992
	[.277]	[.000]	[.561]	[.364]	[.501]	[.475]	[.000]
Firm							
Medium	.732	.727	.823	.273	2.707	.029	1.300
	[.040]	[.371]	[.539]	[.006]	[.002]	[.000]	[.218]
Large	.411	.558	.285	.050	3.489	.034	1.024
	[.000]	[.041]	[.000]	[.000]	[.000]	[.000]	[.885]
Building	3.169	6.502	26.273	16.829	2.221	2.781	3.896
	[.000]	[.000]	[.000]	[.000]	[.001]	[.000]	[.000]
Comerce	1.579	1.163	4.947	4.797	.822	1.616	1.219
	[.000]	[.449]	[.000]	[.000]	[.206]	[.008]	[.082]
Financial	1.264	1.252	3.136	1.041	2.860	3.587	.861
	[.015]	[.273]	[.000]	[.916]	[.000]	[.000]	[.196]
Public	1.437	.756	1.537	.990	5.432	2.676	.742
	[.004]	[.350]	[.155]	[.984]	[.000]	[.000]	[.048]
Other	1.434	1.305	3.037	1.245	2.240	3.040	1.177
	[.000]	[.170]	[.000]	[.538]	[.000]	[.000]	[.141]
Other Ctrl.							
2003	.794	.932	.916	1.240	.903	.676	.587
	[.022]	[.728]	[.660]	[.565]	[.355]	[.014]	[.000]
2004	.745	.802	.507	.869	.666	.569	.606
	[.003]	[.275]	[.001]	[.681]	[.001]	[.000]	[.000]
2005	.488	.323	.375	.496	.450	.426	.408
	[.000]	[.000]	[.000]	[.050]	[.000]	[.000]	[.000]
BA	.504	.721	.375	.489	.337	.275	.332
	[.000]	[.257]	[.001]	[.170]	[.000]	[.000]	[.000]
MG	.764	.629	1.637	2.245	1.060	1.158	.945
	[.028]	[.070]	[.046]	[.078]	[.640]	[.460]	[.691]
RJ	.470	.191	.207	.338	.477	.225	.203
	[.000]	[.000]	[.000]	[.027]	[.000]	[.000]	[.000]
SP	.798	.587	.526	.615	.479	.560	.450
	[.058]	[.034]	[.018]	[.267]	[.000]	[.006]	[.000]
RG	.892	1.135	1.957	1.087	.987	.940	1.229
	[.391]	[.652]	[.016]	[.860]	[.926]	[.786]	[.187]
θ	14.801	75.974	67.243	119.761	3.014	17.375	17.798
	[.000]	[.000]	[.000]	[.000]	[.401]	[.000]	[.000]
Obs.	54590	54590	54590	54590	54590	54590	54590
ln(PLik)	-57141						

Notes: Robust p-values errors in brackets.
Source: Authors' calculations.

Figure 6a: Survivor Function by Firm Size

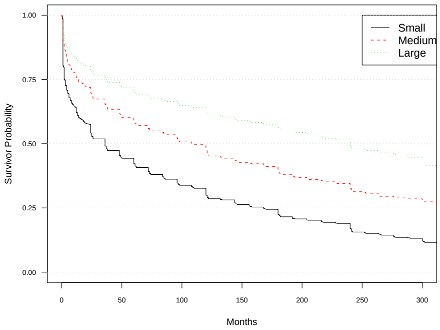


Figure 6b: Survivor Function by Firm Size: Informal

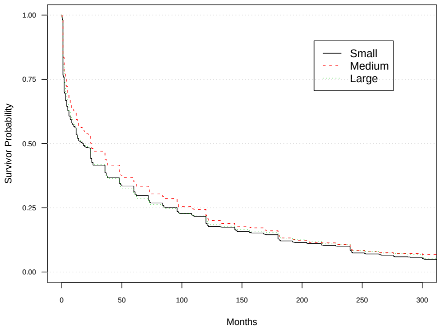


Figure 6c: Survivor Function by Firm Size: Formal

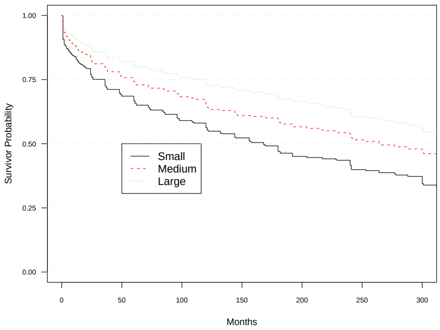


Figure 7a: Survivor Function by Cohort

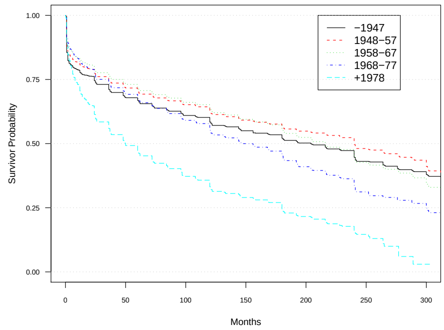


Figure 7b: Survivor Function by Cohort: Informal

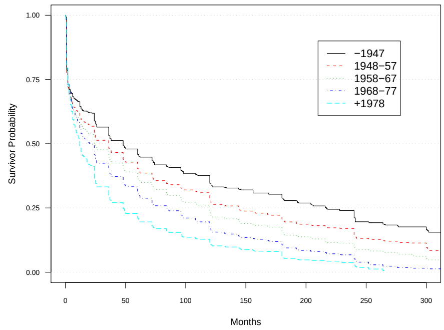


Figure 7c: Survivor Function by Cohort: Formal

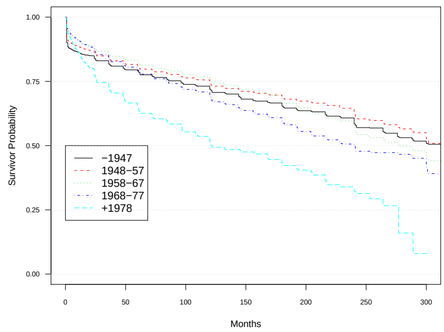


Figure 8a: Survivor Function by Region

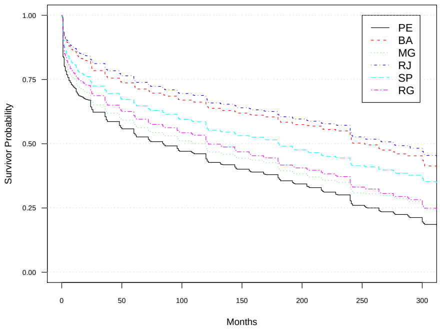


Figure 9a: Survivor Function by Year

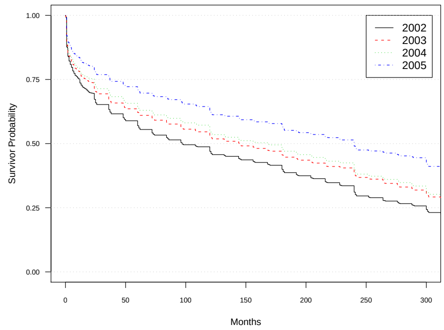


Figure 8b: Survivor Function by Region: Informal

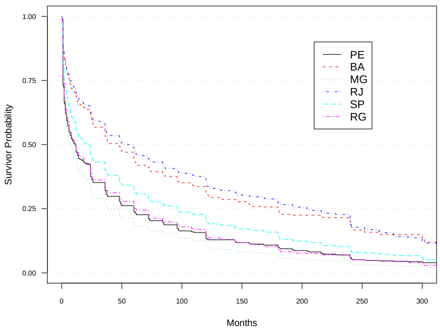


Figure 9b: Survivor Function by Year: Informal

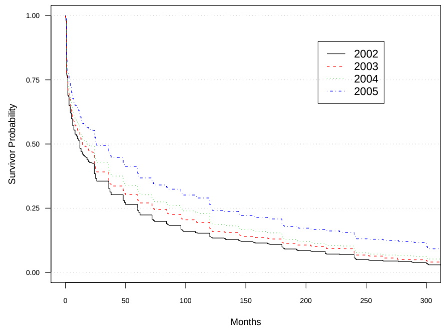


Figure 8c: Survivor Function by Region: Formal

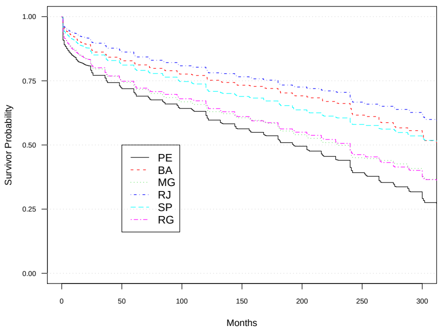


Figure 9c: Survivor Function by Year: Formal