RE-EMPLOYMENT DYNAMICS OF THE UNEMPLOYED IN MEXICO

Angel Calderón-Madrid

Prologue by James J. Heckman

EL COLEGIO DE MÉXICO

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Angel Calderón-Madrid
Professor and Researcher of the
Center of Economic Studies
El Colegio de México

EL COLEGIO DE MÉXICO

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To my sons Emilio and Nicolás

Contents

Part 2. *Programs for unemployed: Casual jobs or better and sustained jobs?*

Prologue

In his prize-winning monograph, Angel Calderon, a leading Mexican microeconomist and microeconometrician, uses state of the art methods to study the dynamics of the Mexican labor market. In two well executed essays, Calderon examines the nature of unemployment in the Mexican labor market and the effectiveness of a training program for the unemployed that was implemented in Mexico in 1994.

His first essay explores the important topic of segmentation of the Mexican labor market and the role of informality in explaining Mexican labor market dynamics. He presents evidence that a sizeable portion of the Mexican labor market excludes individuals who seek employment in it, but cannot attain it. His research shows the importance of accounting for the informal sector in Mexico in analyzing unemployment. He discusses the search strategies used by the unemployed and makes recommendations for improving labor market efficiency.

He shows that the labor market rigidities induced by Mexican law and regulation have serious consequences in creating and maintaining a substantial informal sector. Workers in the informal sector find it is difficult to leave informality once they enter it. Strategies that target those in the informal sector to transit to the formal sector might be very effective. His analysis suggests that it will be profitable to dismantle Mexico's rigid labor codes to free up its labor market and make it more fluid.

The second essay in this volume is a sophisticated evaluation of a training program designed to move Mexican workers out of unemployment. He extends the conventional approach to program evaluation that focuses mainly on the impact of programs on trainee wages and unemployment to look at the impact of the program on trainee weeks of employment. He presents a much more complete evaluation of the program and demonstrates its positive impact. His analysis reverses conclusions from previous analyses about the effectiveness of the program.

His well crafted and well exposited research deserves careful attention by analysts and policy makers. The methodology developed in this work should be applied more widely to study the performance and problems of Mexican labor markets.

James J. Heckman
2000 Nobel Prize Winner in Economic Sciences and
Professor of Economics at the University of Chicago
October, 2010

Preface

Unlike developed economies, in developing ones only a small proportion of unemployed workers can find sustained employment in which they have access to labor rights and social protection. Public policies must therefore shield employees not only from the sort of labor-market malfunctioning that gives rise to prolonged unemployment, but also from the risk of the employees being demoted to low-income jobs that do not provide opportunity to 'learn on the job' and have none of the benefits that a formal worker normally enjoys.

The basic elements one needs in order to understand the nature and relative importance of the unemployment problem in any given developing country, as well as to be able to design an active labor-market policy, are the factors determining the duration of an individual's time in (and out of) employment, together with those that determine the rates of transition from unemployment to employment.

Mexico is an interesting case study for anyone wishing to understand these elements. It shares with other developing countries the many institutional conditions that affect both the likelihood of an individual finding a job, as well as the choices that firms and workers make when deciding between the formal and the informal sectors. These conditions include: a fragmented system of social-security protection in which access to health service is linked to the worker's form of participation in the labor market; the absence of unemployment insurance; a labor legislation protecting employment which is applied unevenly, according to the size of the firm and the sort of activities involved. In addition, it has a wealth of employment and unemployment data available with which to make empirical analyses.

This book approaches Mexico's unemployment problem using panel micro data sets and applying statistical survival analysis. It is divided in two parts. The first part emphasizes that exit from unemployment can be to a different job status (formal and informal salaried jobs, self-employment and out of the labor force) and therefore the natural setting for these estimates is the use of competing risk-hazard models. The second part stresses the fact that the effectiveness of programs targeted to unemployed individuals depends not only on helping them to escape from this status, but also on helping them to find sustained employment that provides opportunity to 'learn on the job'. The natural setting for the estimates presented in this part of the book is multispell hazard models.

The first part uses the National Institute of Statistics (INEGI) quarterly national employment surveys for 2005, 2006 and 2007. These provide information about individuals who were interviewed quartely in up to five subsequent times and provide for each unemployed person, his or her duration in this status as well as his or her movements from unemployment to formal and informal jobs, to self-employment and out of the labor force. The second part deals with the effectiveness of active labor market policies targeted at unemployed workers without adequate job-related skills. These individuals represent a major problem in developing countries. It is unlikely that they can increase their employability prospects without government help. And this is partly due to to market failures in labor and credit markets and partly to the lack of resources at their disposal and to the difficulty they have in finding an employment that allows them to 'learn on the job'.

The most common instruments available to help them are publicly sponsored training programs of short duration. These are intended to be more than an income support mechanism for their beneficiaries. Their aim is to help individuals get back to work and to help them to achieve the jobs in which they can last and improve their skills. We posit in part two of this book that evaluation studies dealing with the performance of this kind of programs in developing countries have not adequately dealt with their impact on beneficiaries' subsequent employment histories. We show there that the impact of a training program on the reemployment dynamics of its beneficiaries must explicitly consider two questions, in addition to asking how quickly individuals find a job after their training. The first question is, were they able to increase the time employed in their first post-training job? The second, did they need less time to find another job, if the first post-training job was lost? We work with a set of data set collected in 1994 for an evaluation of a Mexican training program targeted at the unemployed. It is the only one which provides appropriate longitudinal data for representative samples of beneficiaries of the program and of eligible individuals who did not participate in it. This is in spite of the fact that this kind of program has been one of the most important active labor market policies in the last fifteen years in Mexico.

The first part of this book originated in a paper I prepared for the "The Third Conference on Employment and Development". held in May 2008 in Rabat, Morocco and organized by IZA (The Institute of Labor Studies of Bonn, Germany) and the World Bank. After doing further work on it, I submitted it for the 2008 NATIONAL BANAMEX PRIZE IN ECONOMICS, where the FIRST PLACE RESEARCH CATEGORY was awarded. Finally in March 2009 the version of the chapter included in this book was presented at the seminar organized by the Bank of Mexico's Research Department, whose members were kind enough to comment on it.

In 2001 I won a competitive bidding process to conduct a one year research project on: the Evaluation of Training Policies in Latin America, which was coordinated by James Heckman and Gustavo Márquez and sponsored by the Inter-American Development Bank Research Network.

The work presented in the second part of this book is a revised version of the result of this project, in which I was fortunate to have Belem Trejo as a coolaborator and the research assitance of Gonzalo Rangel. It was presented in a number of seminars organized by the IADB Research Network in Chile, Washington and Brazil where I benefitted from the comments by James Heckman, Petra Todd and Jeffrey Smith; at "The 10th International Conference on Panel Data", Berlín, Germany in July 2002 and at the UIA seminar in Mexico City in September 2003, where Robert Lalonde discussed it and provided useful feedback.

Part 1

Unemployment duration in Mexico: Its determinants and implications for the labor market segmentation controversy and public policy design

1.1. Introduction

This study uses Mexico as a case study to analyze the determinants of the unemployment duration of workers with different characteristics, and of the transition rates from unemployment to formal on informal jobs, self-employment and out of the labor force. These, together with the determinants of the transition rates from employment and out of the labor force to unemployment, are the required components for understanding the nature and relative importance of the unemployment problem in a middle-income developing country and for designing active labor market policies. They are also required to answer questions related to the impacts of institutional reforms on the functioning of labor markets; for example: does a change in legislation that decreases the dismissal costs of employees, reduce the duration of unemployment and increase the relative size of the formal sector in the economy?

Mexico is an interesting case because it shares with many developing countries institutional arrangements that affect firms' and workers' choices between the formal and informal sectors, *e.g.*: no unemployment insurance, labor legislation favoring employment protection, unequal enforcement of this legislation varying by firm size and by types of activities, and a fragmented system of social security protection in which access to health services is linked to one's form of participation in the labor market. In addition, the richness of Mexico's its employment data allows us to work with a data set appropiate for the required analysis. By virtue of recent modifications to Mexico's questionnaire on quarterly employment, it is possible to measure (from 2005 onwards) with precision how much time unemployed workers spent in job searching before finding a job, or before moving out of the labor force. For those who got jobs, we know how they contacted their new employers and what kind of status their new jobs had (formal, informal, salaried, or self-employment). Also available are characteristics of the workers (education, age, civil status and number of children under

18 years old), if other members of their households had jobs, and information about their previous job histories; most notably, if their previous jobs were formal or not, and their reasons for separating from their jobs. It also captures if unemployed individuals received lump-sum payments associated with an employer-initiated job separation.

We contribute to the controversy about how segmented the Mexican labor market is by presenting evidence suggesting that a worker's search intensity decreases for a formal job, and increases for an informal job with increasing lengths of unemployment. This is something that no available analytical and empirical studies addressing labor market segmentation topics have addressed since all of them have focussed on relative wage differences between formal and informal job statuses. We also address other related questions, among which are the following: how unemployment duration is affected by economic expansion are some job searching methods more effective in helping individuals escape unemployment faster, and are they equally effective for escaping to the formal and informal sectors? How are the workers' durations of unemployment and job status destinations related to their having been formal workers in their previous jobs? Do workers who are laid off from their previous jobs and receive severance payments, take longer to find jobs and do they find better jobs relative to those that received no severance payments? Is there evidence suggesting that a worker's search intensity decreases with increasing lengths of time in unemployment or that of job offers arrive less frequently, the longer a worker is unemployed?

We analyze determinants of the duration of unemployment spells of individuals who were without jobs, but were looking for them during the first quarters of 2005, 2006 and 2007. We use information obtained from a quarterly employment survey that uses a rotating panel of workers and substitutes 20 percent of the interviewed persons each quarter.[1] Our empirical analysis is based on methods to analyze time-to-event data (survival analysis models or competing risks hazard functions) to estimate determinants of the duration of unemployment and people's exits to four different mutually exclusive destinations: formal jobs, informal paid jobs, self-employment, and out of the labour force. Because the cohorts of unemployed individuals belong to years with different rates of economic growth –the year 2006 had economic expansion with a real rate of growth that was twice the corre-

[1] Surveys applied at periodic dates to samples of the labor force over-represent individuals with longer unemployment spells. This is the so-called 'stock sample bias' to which samples based on registers for the total population are not subject. The Mexican panel survey enables us to mitigate this bias; it allows for the measurement of unemployment spells experienced between interviews by individuals employed at the time of the first and second interviews of the year. This is done by means of complementary questions in the second quarter's questionnaire: which measure, their job tenure in their current jobs and the date of job separation from their previous positions.

sponding figures for 2005 and 2007– we can assess if escape rates out of unemployment increased, and if the hazard of exiting the labour force to non participation status decreased with the upswing of the economic cycle.

Our empirical analysis controls for individual and household characteristics and for job search methods used by unemployed individuals. It assesses the extent to which counting with a "financial cushion" provided by a lump-sum payment for separation from their previous employment, allows workers to look longer for a job with desired characteristics relative to those who do not count with such a "cushion".

The results of this paper are consistent with the contention that, after a period of job searching, a subset of formal workers that becomes unemployed, fails to obtain acceptable job offers to remain formally employed, in despite lowering their reservation wages. Empirical hazard rates out of unemployment for these individuals indicate that after an initial phase of unsuccessful job searching in the formal sector, their search efforts concentrate in the informal segment of the market where these workers end up accepting job offers which lack the benefits associated with formal employment without receiving any compensation for this lack of benefits. This contrasts with what is expected in frameworks in which the formal and informal segments of the labor market are integrated -*e.g.* Maloney (1999). In these frameworks, workers that have worked in the formal sector switch to an informal job because they are offered a wage premium above that which they could expect to earn in a formal job.[2]

This paper is structured in six sections in addition to this introduction. Section 2 discusses relevant theoretical developments as a background for our empirical work. Section 3 describes the main features of the Mexican labor market and Section 4 the data set. Section 5 presents the statistical model we used in this research. Section 6 discusses our results, and Section 7 presents concluding remarks.

1.2. Theoretical background

Models of labor market segmentation and dualism aiming to understand why some job seekers in developing countries are employed in the formal

[2] We explicitly test the hypothesis that formal job seekers that become informal employees do not earn more than what they would have earned, if they had remained in the formal sector. For this purpose, we use statistical matching methods to 'pair' two groups of unemployed individuals whose previous job was in the formal sector. One group is composed of those that find jobs in the formal sector, and the other by those that become informal employees. These two groups are not statistically different from each other in their observable characteristics. This matching procedure is conducted to obtain hipothetical earnings that would have been paid to workers that became informal employees if they had, instead, remained in the formal sector.

sector while others accept informal jobs, assume payment of efficiency wages in the formal sector (i.e. of wage levels above market clearing level paid to increase workers productivity and to attract a larger pool of applicants from which employers can hire more selectively) and barriers to enter into the formal sector (*e.g.* unions, minimum wages, non-competitive hiring in the public sector, excessive regulation and national labor codes). As a result of these kind of assumptions, "good" jobs (those in the formal sector) are rationed, and some unemployed workers who would like to have a formal job, get no job proposals from employers in that sector. Implicit in this approach is the presumption that the flow of workers between formal and informal jobs, is small after an unemployment spell, (Dickens and Lang, 1985). This follows from the view that opportunities in the formal sector are limited for unemployed persons and informal workers, and that once workers get formal jobs, they stay in that sector for the rest of their working life.

Stylized facts of the job market in Mexico and in other middle-income transition economies indicate that –contrary to what is assumed in models with labor market segmentation– a lot of mobility exists between jobs of different statuses. Therefore, for their analysis, an explicit modelling of job status transitions and their determinants is required. This is what recently developed models for understanding workers in labor markets in developing countries, do. These models have incorporated features that extend the approach initially put forth in Mortensen-Pissaridis (1994). This approach takes as its point of reference an explicit modelling of information asymmetries in labor markets and the relevance of flows of workers between job statuses. Hence, their analysis explicitly considers that time and resources are required for workers to find appropriate jobs, and for firms to find appropriate workers. Main assumptions of this approach are to derive from optimization criteria that unemployed individuals have a "reservation wage", and that job offers with wages below this level are turned down as a result of a trade-off between the prospects of future benefits, and the cost of foregoing earnings. Another assumption of this approach is that wage offers occur randomly from the point of view of the individual. As stressed by Eckstein and Van den Berg (2007), with these two components, it is possible to divide exit rates out of unemployment, and the mean unemployment duration, into choice (voluntary) and chance (involuntary) components. Specifically, the hazard rate for leaving unemployment to employment implied in these models is the product of a job offer arrival rate, and an acceptance probability, given the arrival of a job offer.[3]

[3] Since the hazard rates out of unemployment can be fully characterized by the parameters of an analytical model which is based on the determinants of the agents' decisions problems, and exogenous shocks (i.e. derived from first principles), they can

In models that apply this approach in a developing country context (Boeri and Garibaldi, 2006; Albrecht, Navarro and Vroman, 2006; Galiani and Weinschelbaum, 2006; Satchi and Temple, 2006; and Zenou 2008), search strategies of workers and employers determine matches in the formal and informal sectors, given job creation and destruction rates in each sector. Implicit in these models is the assumption that, in a stationary environment, formal and informal labor markets are integrated.[4]

For example, in the analysis by Albrecht, Navarro and Vroman (2006), the workers' search behavior take place in an environment with formal and informal jobs. They derive conditions under which a worker is indifferent between searching for a job in the formal or informal sectors. The inclusion of the assumption of heterogeneity of workers in terms of potential productivity implies that, in their stationary environment, workers whose potential productivity is below a threshold would only be informal job searchers, those above a second threshold would only be formal job searchers, and those whose potential productivity is within these two thresholds, would be "switchers" between formal and informal jobs. In their model, threshold changes result from exogenous shocks.

In spite of assuming integrated labor markets, wages in these models can diverge between *ex ante* similar workers because of information frictions, luck in the job search, the matching process, etc. This type of wage inequality inherently associated with frictions has been called "frictional wage dispersion" (Hornstein, Krusell and Violante, 2008).

Empirical studies for developed economies with no informal labor markets which include information on effective time spent on job search activities and the intensity of these activities, indicate that search intensity decreases with the length of the unemployment period (Barron and Gilley, 1979). Other studies posit that there is a "systematic search", where individuals first look at the locations that are best according to a prior, and if those searches are unsuccessful, they proceed to other locations, typically lowering their reservation wage along the way (Rogerson, Shimer and Wright, 2006); that search efforts affect the job arrival rate (Ljungqvist and Sargent, 1998); that search strategies –and not only reser-

be used to predict how alternative policy interventions affect behaviors.

4 When formal and informal labor markets are integrated, an unemployed worker is indifferent between earning a reservation wage in a formal job, or this reservation wage plus a compensation or "wage premium", in an informal job. (This differential in wages compensates for non-pecuniary benefits associated with being formal that a worker will not have, if a job is accepted in the informal sector, *viz.* labor legislation rights, access to a bundle of institutional social security services which include health care, life insurance along with work liability and disability insurance, day care centers for children, retirement pension, and housing funds), etc. That is, as in the case of Khandker 1998, unemployed workers maximize utility rather than income.

vation wages– change as time in unemplyment increases; and that search costs increase as workers fail to obtain acceptable offers from their closest and better known potential working places. In turn, a number of elements of job searches which have been the basis for empirical analysis in developed economies, have not yet been incorporated in models for labor markets in developing countries: For example, Rendon (2006) looksat risk adverse individuals, wealth accumulation and borrowing constraints, while Lentz and Tranaes (2001) look at the depletion of resources to finance their employment searches. Lastly, search methods for finding formal and informal jobs, and their relation to exits out of unemployment, are topics previously addressed for developing countries by Márquez and Ruiz-Tagle (2004), Woltermann (2004) and Calvó and Ioannides (2005), but have not been incorporated yet as part of job search models for developing countries.

As discussed below, Mexico shares with many developing countries a labor code that stipulates that, in case of dismissals of individuals, the employer must make lump-sum severance payments. Lentz and Tranaes (2001) have shown that workers who possess liquid assets to finance their job searches, take longer to accept a job. Along with this result from their work, we postulate that job searching is a productive activity in which an individual may invest funds and expect a significant relationship between the availability of liquid assets and escape rates from unemployment. That is, we expect a negative effect on rates of escape from unemployment that can be attributed to lump-sum payments obtained when separating from their previous job relative to those who received no compensation. This is because we expect the former to "afford" longer search periods and to have their search efforts increase as their liquid wealth declines.

This is not the only reason why a negative relationship can be expected between job search time, and the availability of liquid resources obtained from being fired from a previous job. Another reason is due to the stigma attached to having been dismissed from their jobs. Hence, if asymmetric information prevails, dismissed workers might send a bad signal to potential employers. This implication of asymmetric information in the labor market has been analyzed in a pioneer work by Gibbons and Katz (1991). In their analysis, employers do not have a clear perception of the workers' productivity when they consider hiring a new worker, but they can know their employment story. On the basis of this information, they form expectations of worker productivity. Canziani and Petongolo (2001), in an extension of this analysis, show that these sources of information asymmetries imply lower job finding rates for dismissed workers relative to unemployed individuals that left their jobs voluntarily. Kugler and Saint-Paul (2004), further extended this framework to consider what happens when dismissal costs of employees are included in this scenario. They show that the shadow cost of hiring workers increases when the likelihood of job termination payments enters in the employers' considerations about offering job. Hence, their result is consistent with a lemons story; as these costs increase, firms increasingly prefer hiring workers with good a employment history over those without one.[5]

1.3. Unemployment and informality in Mexico

In this paper an unemployed individual is defined as an individual without a job, but looking for one, whereas an individual without a job and not looking for one, is identified as being out of the labor force. A formal employee is defined as a wage-earning person registered in public social security agencies or in retirement pension fund agencies. Informal salaried employees, in turn, are defined as employees not registered in these agencies, while the self-employed are non-wage earners working on their own (including business owners with less than three employees). Because of their registration in these agencies, formal workers have access to a bundle of services which are partly financed with payroll taxes. These services include health care, life insurance, work liability, disability insurance, and retirement pensions.[6] Informal salaried workers cannot exercise their labor rights because they are unable to offer evidence of a working relationship with their employers and have no access to health care services or pension and housing funds administered by the government for formal workers.

Mexico shares with many developing countries a labor code that fixes severance payments in case of employer initiated separations of workers. The severance payment is equivalent to three months' pay plus 20 days of salary per year of service. If the employee has remained with the same employer for 15 years, he/she will not receive a seniority premium. Non-wage costs of formal jobs (taxes, non-wage costs and administrative procedures), which represent up to 40% of the wage bill together with the cost of fulfilling labor codes, are often seen as a major cause of a large informal sector. Figures obtained from household surveys for 12 Latin American countries in which the existence or absence of social security contributions is registered for each employee in the sample, indicate that the degree of formalization of salaried workers in Mexico is below average. In contrast to Chile, Uruguay, Brazil and Argentina, where more than half of salaried workers hold formal

[5] Kugler and Saint-Paul (2004) show that firms prefer to offer jobs to already employed workers relative to those looking for a job, and among these latter ones, to those not subject to dismissal costs, or to those that lost their job due to end of contracts.

[6] In Mexico there is also an official agency in charge of operating housing funds for formal employees.

jobs, only 42 percent of employees in Mexico are formally employed. This figure is slightly above countries with much lower levels of development such as Peru, Bolivia and Ecuador (Galiani and Weinschelbaum, 2006). By contrast, the share of informal salaried workers and of the self-employed in the Mexican urban labor force (around 28 and 30 percent, respectively) is relatively large for a middle-income emerging economy.[7]

Relative to the figures from developed countries, aggregate open unemployment rates in Mexico are low below 4% of the active labor force during the period 2005-2007. Little is understood about the nature and relative importance of the unemployment problem in a country by focusing only on open unemployment rate figures -even when the focus of analysis is on corresponding rates for subsets of the labor force with specific characteristics or located in different geographic areas of the country. For example, without explicitly stating why, it is common to attribute these relatively low aggregate rates to the lack of unemployment insurance, which makes unemployment unafordable for most participants in the labor market.

As stressed in this paper, what is required is an analysis of the duration of unemployment spells and of their determinants. For example, unemployment rates differ substantially between groups of individuals and between geographic regions of the country. This does not imply that low rates of unemployment necessarily coincide with states and groups where the duration in unemployment is low. Conversely, as the results in the empirical section of this paper indicate, two states that coincide in unemployment rates can have very different escape rates from unemployment. This is because an explicit relationship exists, for any given flow of entry into unemployment, between open unemployment rates, and duration in unemployment. Hence, in a given region, the flow of entry into unemployment might not be a matter of policy concern (*e.g.* resulting from an efficient enhancing restructuring in the economy) whereas flow out of unemployment might be (*e.g.* vulnerable groups may be likely to stay unemployed for long periods).

1.4. The data

During many years the Mexican National Institute of Statistics, Geography and Informatics (INEGI) conducted a panel-linked quarterly employment survey (ENEU). This survey did not lend itself to a formal analysis of unemployment duration and job searching strategies. The information

[7] The majority of informal salaried employees work in informal firms which tend to be small in size; the remainder may have a working relationship with a formal firm that fails to register all of their workers in the social security agency and evades other obligations that it should be meeting by law.

concerning the precise time required for finding a job was unavailable. How unemployed individuals looked for jobs was also not part of the information asked to respondents. In the first quarter of 2005, INEGI's questionnaire was modified, and a more complete employment survey (*Encuesta nacional de ocupación y empleo*, ENOE) has since been conducted.

This new survey interviews a rotating panel of workers and substitutes 20 percent of the interviewed persons each quarter. During the second quarter of each year, incorporates additional questions that enable us to measure the effective time required by each worker who found a job after an unemployment spell. We worked with three sets of two-quarters balanced panel data set. This implies an attrition of 20% of the individuals interviewed in the first quarter of each year, namely those that were in their fifth interview. (Likewise, we do not include those incorporated after the first interview of the year).

When individuals are unemployed during their first interview of the year, they are asked about how long have they been searching for a job. During their subsequent interview in the second quarter of that year, they are asked about their job tenure in their current job. This information is required to measure precise exit times from unemployment for those that found a job before their second interview. In addition, for individuals employed at the time of the first and second interviews of the year, it is possible to identify if they went through an unemployment spell during the second quarter of the year. If they did, it is possible to know the duration of these spells. This is done by means of two questions included in the second quarter's complement of the questionnaire: their job tenure in their current job and when they left their previous job.

We restrict our analysis to unemployed male workers between 18 and 65 years old with previous job experience. The cohorts correspond to the first quarter of 2005, 2006, or 2007, and the total initial number of respondents was 6 322. For those finding a job on a subsequent date, we not only have information regarding the time required by each of them to find a job, but, also, what kind of status this job had (formal or informal, salaried, or self-employment). If they were not employed in subsequent quarters, we have two cases: dropping out of the labor force, or still searching for a job. Among other questions, they answer if, in their previous job, they had access to a bundle of institutional social security services, partly financed by their payroll taxes: That is, if they had a formal or informal job. They also respond about whether the reason for leaving their last job was that they were laid off, whether they left voluntarily, or not.

In table 1 a transition matrix captures the structure of the data set. The columns in this table indicate destinations in subsequent quarters, and the rows classify individuals according to their previous job status. Their new status in the subsequent quarter could be as a formal or an informal employee, self-employed, out of the labor force, or still unemployed. In turn, their job status in employment before their unemployment spell could have been one of two types: formal or informal (included in this latter are non-formal wage earners and the self-employed). This table shows that while 44% of the previously formal workers found a new job within the same status, 26% ended up as informal employees and 5% as self-employed. Stated differently, out of the totality of unemployed workers that were previously formal and that found a job, 31% of them moved to the informal sector.

Table 1
Unemployed male workers with previous job experience
Transition matrix

	Job status in new employment after					
	Formal	*Informal*	*Self-employment*	*Out of the labor force*	*Remained unemployed*	*Number of observations*
TOTAL	1551	2856	359	745	811	6,322
Job status in previous employment before unemployment spell:						
Formal	44.75%	26.05%	5.36%	6.70%	17.15%	1,866
Informal or Self-employment	16.07%	53.19%	5.81%	13.91%	11.02%	4,456
2005						
Formal	40.67%	27.39%	5.21%	6.22%	20.50%	595
Informal or Self-employment	16.03%	51.69%	6.67%	14.38%	11.24%	1,335
2006						
Formal	48.66%	25.83%	3.94%	6.46%	15.12%	635
Informal or Self-employment	16.27%	55.55%	5.93%	12.11%	10.15%	1,586
2007						
Formal	44.65%	25.00%	6.92%	7.39%	16.04%	636
Informal or Self-employment	15.90%	52.05%	4.95%	15.37%	11.73%	1,535

Note: Rows add up 100 per cent. Source: INEGI, *Encuesta nacional de ocupación y empleo.*

Our interest in this study is in how quickly individuals escape unemployment which is implicitly given by the evolution over time of their survival rates in this state. This requires a precise measurement of how many weeks unemployed workers spent searching for a job before finding one, or before moving out of the labor force. It also requires including the time spent job searching by individuals who started a spell of unemployment and were still in the same unemployed status when they were last interviewed.[8] By virtue of recent modifications to Mexico's questionnaires for quarterly employment surveys, it is possible to obtain (from 2005 onwards) this information (length of unemployment on the day when they were interviewed in the first quarter of the year, plus additional weeks required to exit unemployment).[9] In section 1.6. of this paper a detailed and rigorous analysis of survival rates in unemployment is presented. In this stage of analysis of the raw data obtained from the employment surveys, it is possible to visualize implied survival rates in unemployment by means of the so-called 'Kaplan Meir estimator'. This is an actuarial non-parametric estimator commonly used in the elaboration of life tables by demographers. It represents exits out of the unemployment state as a percentage of individuals "at risk". As part of this latter subset, it incorporates information provided by those that remain in unemployment at the time of their last interview and this is identified as "right-hand censored data" (Kiefer, 1998). Table 2 shows that 70% of unemployed individuals with previous job experience escape unemployment in less than four months, and that one out of four unemployed individuals are still without a job after five months.

In table 3, the distribution of characteristics of respondents is presented. The first categories in which individuals are grouped are age, levels of educational achievement, marital status (grouped in three subcategories: single, married with children under 18, married with no children, or married with children older than 18), and if they are located in an urban or rural area. Two variables were constructed in order to capture whether or not unemployed individuals are able to finance a longer job search to obtain a better job match. The first variable captures whether or not other adults

[8] If we do not include information corresponding to individuals with unfinished spells (so-called censored data) a measurement bias is introduced against people with longer spells in unemployment.

[9] Surveys applied at periodic dates to samples of the labor force over-represent individuals with longer unemployment spells in the population. This is the so-called 'stock sample bias' to which samples based on registers for the total population are not subject. The Mexican panel survey enables us to mitigate this bias; it allows for the measurement of unemployment spells which occurred between interviews for individuals who were employed at the time of the first and second interviews of the year. This is done by means of complementary questions in the second quarter's questionnaire asking about their job tenure in their current job and the date they left their previous job.

in the household are working, and the second, whether or not they received a lump-sum payment for separation from their previous job. Individuals are also classified according to length of unemployment on the day of their interview in the first quarter of the year. We classified their responses in four categories: less than a month; more than one month, but less than two; between two and four months, and more than four months. Finally, for those finding a job, how they contacted their new employer is classified in one out of five mutually exclusive categories (if they directly contacted businesses, if they responded to an advertisement for a job on the Internet, on the radio or in a newspaper; if they asked family or friends to recommend them for a job or to keep them informed about possible jobs; if a job was offered to them, or if they got it through a government employment service, through a private employment agency, or through another similar method).[10]

Graph 1 shows real levels of GDP growth (relative to its level the same quarter one year before). As is clear from this graph, the year 2006 represents an economic expansion: during the first quarter of the year, GDP grew twice as fast as the rate of growth during the first quarters of 2005 and 2007.

Table 2

Unemployed male workers with previous job experience
Kapplan Meir survival rates in unemployment
2005-2007

Interval (in weeks)	*Escape from unemployment*		
	At risk	*Escape*	*Survival rate*
less than 8	6322	2789	0.56
8-10	3533	299	0.51
10-12	3234	738	0.39
12-14	2496	244	0.36
14-16	2252	521	0.32
16-18	1731	552	0.29
18-20	1179	321	0.26

Source: INEGI, *Encuesta nacional de ocupación y empleo.*

[10] For those opting out of the labor force, for those that remained unemployed, and for those that went to self-employment, the survey does not ask this question. Hence, for estimation purposes a different question is used with this subset of individuals. The question asked is about how they looked for a job.

Table 3
Unemployed male workers with previous job experience
Descriptive statistics

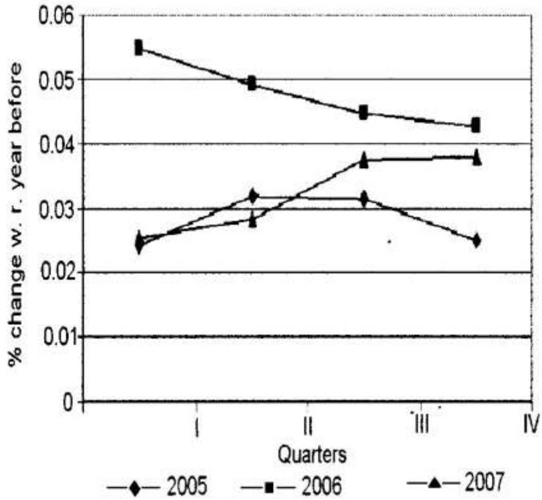
	Remained unemployed (%)	*Formal salaried* (%)	*Informal salaried* (%)	*Self-employment* (%)	*Out of labor force* (%)
Age					
18 to 22 years old	21.58	26.95	22.76	7.80	36.78
23 to 28 years old	26.76	26.43	20.17	17.55	19.46
29 to 35 years old	15.41	20.89	20.48	21.17	8.05
36 to 44 years old	16.15	14.44	18.03	26.18	7.65
45 to 65 years old	20.10	11.28	18.56	27.30	28.05
Education					
Elementary school	12.70	17.15	47.69	33.70	20.27
Secondary school	23.43	38.10	31.09	28.13	23.36
High school	20.47	23.15	11.97	15.32	25.50
More than high school	43.40	21.60	9.24	22.84	30.87
Marital status and children					
Single	58.57	43.39	34.03	17.83	63.76
Married or head of household and children under 18	20.72	35.14	43.84	56.27	12.21
Married or head of household without children or children older than 18	20.72	21.47	22.13	25.91	24.03
Worker in the household					
No	27.00	30.37	38.31	48.47	21.21
Yes	73.00	69.63	61.69	51.53	78.79
Search strategy followed					
Attending to the establishment directly	73.04	28.24	27.24		

Table 3
(continued)

	Remained unemployed (%)	*Formal salaried* (%)	*Informal salaried* (%)	*Self-employment* (%)	*Out of labor force* (%)
By newspaper, radio or internet	10.79	23.21	5.57		
By friends or family members	6.32	42.23	48.35		
Job was offered to you	-	3.68	17.65		
Gov. emp. service, private emp. agency and others	9.86	2.64	1.19		
Previous job was formal					
No	60.54	46.16	82.98	72.14	83.22
Yes	39.46	53.84	17.02	27.86	16.78
Reason why last job was left					
Other	54.99	68.02	50.91	64.62	83.49
Lay off	45.01	31.98	49.09	35.38	16.51
Urban area					
No	12.95	14.83	40.34	25.91	13.83
Yes	87.05	85.17	59.66	74.09	86.17
Lump-sum job separation payment					
No	95.07	96.13	97.97	94.43	87.65
Yes	4.93	3.87	2.03	5.57	12.35
Previous lenght of unemployment					
0 to 30 days	41.80	75.24	84.21	79.39	42.82
More than 30 to 60 days	25.40	13.93	8.26	12.26	29.80
More than 60 to 120 days	18.37	6.90	5.22	4.74	16.91
More than 120 days	14.43	3.93	2.31	3.62	10.47
No. of observations	811	1551	2856	359	745

Source: INEGI, *Encuesta nacional de ocupación y empleo.*

Graph 1
GDP growth



In view of the different levels of GDP growth which occurred each year, for estimation purposes, we classified the sample according to the year in which each cohort was interviewed. Mexico is divided in 32 political states. GDP growth, unemployment rates and access to formal sector jobs vary significantly across them. The northern states, for example, have larger shares of formal, relative to informal, sectors. By contrast, economic activities in the southern states are less affected by shocks originating in the US. Hence, in addition to a location category depending on urban or rural characteristics, we aggregated the sample in 32 groups according to where the person lived.

1.5. Statistical models for survival analysis

◇ Hazard and survival functions

The point of departure of survival analysis is the definition of a non-negative continuous random variable T, which represents the spell duration (duration of unemployment) with a density function $f(t)$ and a cumulative distribution function, $F(t)$. This latter is defined as the probability that an unemployment spell lasts less than t units of time. The survival function, $S(t)$, equal to $1-F(t)$, is defined as the probability that the unemployment spell will equal or exceed a period of length t:

$$S(t) = \Pr(T >= t) \tag{1.1}$$

For any specification of t in terms of a density function, there is a mathematically equivalent hazard function, $h(t)$, which is the conditional density of T given $T > t > 0$; *viz*:

$$h(t) = \left(\frac{f(t)}{1 - F(t)}\right) \tag{1.2}$$

the hazard rate of $T, h(t)$, can be interpreted as the transition rate at time t given survival in the state up to at least t. To see this, note that for short $\Delta t > 0$

$$h(t)\Delta t = \left(\tfrac{f(t)\Delta t}{1-F(t)}\right) \approx \tfrac{\Pr(T\epsilon[t,t+\Delta t)}{\Pr(T\succeq t)} = \Pr(T\epsilon[t,t+\Delta t)|\Pr(T \succeq t) \tag{1.3}$$

is the transition probability in the short interval $[t, t + \Delta t)$ given survival up to the start of the interval. Notice that the hazard can alternatively be expressed as the logarithm change of the survival function and, conversely, that the hazard function allows us to estimate the survival function by:

$$S(t) = \exp[-\int_0^t h_u du] \tag{1.4}$$

◇ Hazard functions and censored data

Hazard functions have the distinct advantage of handling survival periods corresponding to individuals that started a spell of unemployment and were still in the same status when they were last interviewed.[11] If we do not include information corresponding to individuals with unfinished spells (so-called censored data) in our estimations, we throw away part of the data set and introduce a serious bias against people with longer spells of unemployment.

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[11] These would constitute a problem for a standard regression model where the dependent variable was the length of the spell of unemployment.

1.5.1. *Competing risks specification*

When there is only one unemployment spell, but more than one possible destination out of unemployment, a competing risks specification of hazard functions is required (Van den Berg, 2001). In the case analyzed in the next section, a person who is unemployed can find a job as a formal or informal employee, become self-employed, or go out of the labor force.

To specify this, let there be M possible job status destinations out of unemployment. Then, there are M random variables, t_{uj}, associated with each state, indexed by m (That is, when an individual is unemployed, there are M "latent exit times"). We can now state that the density function of exit times from unemployment into state j is $f_{um}(t_{uj})$ and that the total of survivals in t, that leave unemployment is the sum on m of those who leave this state in order to go to the destiny m:

$$h(t) = \sum_{m=1}^{M} h_{um}(t_{uj}) \qquad (j = 1, ...M; \quad j \neq u)$$

In this formula, $h_{um}(t_{uj})$ is defined as the hazard function associated to a specific destiny and finally, we have the hazard function conditional on survival up to time t given by:

$$h_{um}(t_{uj}) = f_{um}(t_{uj}) / \exp[-\int_{t_{uj}0} h_{um}(u)du] \qquad (j = 1, ..., M; \quad j \neq u)$$

◇ Competing risks and censored data

For estimation purposes, we assume that unobserved determinants of the transition rates to the possible destinations are mutually independent. [12] If this assumption holds, it is a valid procedure to estimate competing risks hazards with one hazard function for each possible destination, as if the only destination out of unemployment was the one estimated in the corresponding hazard function. This procedure requires including individual departures to a state different than the one corresponding to the function, as part of the censored data set.

[12] If this assumption does not apply, the right-censored is dependent, and a more elaborate estimation is required. *Cfr.* Heckman and Singer (1985).

1.5.2. *Hazard function specifications*

For estimation purposes, in the following section we work with 'mixed proportional hazard' specifications -also called Cox proportional hazards. This type of specification has two parts: a 'baseline' hazard (which captures time dependence in a common way for all individuals) and a 'systematic part'. This latter takes the form of an exponential function and depends on a number of observed co-variates, X. (which in our estimations are an individual's observed characteristics, and year and location specific dummies). Thus, the hazard rate is multiplicative in all the separate elements of the covariates:

$$h_{um}(t_{um}) = h_{0m}(t)\exp(\beta' x) \qquad (j = 1, ..., M; \qquad j \neq u) \quad (1.5)$$

where x is the vector of measured explanatory variables for the individual and β is the vector of unknown regression parameters associated with the explanatory variables. (This vector is assumed to be the same for all individuals). The parameters in β are estimated with maximum likelihood methods, which accounts for censored survival times. The baseline hazard, $h_{0m}(t)$, captures the common hazard among individuals in the population. The hazard ratios, computed by calculating the exponential of the parameter coefficients, are useful in interpreting the results. If the hazard ratio of a co-variate is larger than 1, an increment in the factor increases the hazard rate. If the hazard ratio is less than 1, an increment in the factor decreases the hazard rate.

As stated in the review of job search models presented in section 2, hazard rates are determined by variables that affect job offer arrival rates, and by those that determine an individual's probability of acceptance of a job offer. In accordance with these models, the right-hand side component of (1.5) must include, in a reduced form, variables that are expected to affect escape rates out of unemployment *via* these channels. These are specified in the following subsection. The length of unemployment in the hazard functions estimated and discussed next refers to the calendar time after the first interview of an individual (the first quarter of the corresponding year). Hence, the length of unemployment prior to the day of the interview in the first quarter of the year is included as a covariate in vector x.

Since our analysis considers exiting unemployment to one of four mutually exclusive destinations (formal or informal employee, self-employed or out of the labor force), four hazard functions, each one with a specification as in (1.5), are estimated and discussed in the following section.

◇ Unobserved heterogeneity

In the specification (1.5), sources of observed individual heterogeneity affecting hazard rates are captured with the vector x, which in our estimations represent an individual's observed co-variates, and year and location specific dummies. The presence of unobserved (or omitted) heterogeneity between individuals can bias the coefficients estimation of the explanatory variables in the hazard model and cause an overestimation of the negative duration dependence (see Van den Berg, 2001). This is because people who have a high unobserved random component are more likely to experience the event of interest early, so that the sample of individuals that survive is a selected sample with relatively small random effects. That is, on average, individuals with relatively high hazard rates for reasons unobserved by the analyst (*e.g.*work ethics, lack of precautionary savings or higher intertemporal rates of return) leave unemployment first. Hence, samples of survivors in unemployment are selected. If this sample selection problem is important, it must be adequately dealt with. Most notably, negative duration dependence at the individual level, and unobserved heterogeneity, both lead to negative duration dependence of the observed hazard rate, but they have different policy implications. Negative duration dependence implies that emphasis should be put on the prevention of long-term unemployment (pointing to the usefulness of policies aimed at intervening long before individuals become long-term unemployed). This type of policy, however, will be inadequate if unobserved heterogeneity is the cause of negative duration dependence of the observed transition rate. In this case, policies should be aimed at the screening of the newly unemployed.

We also estimate a variant of (1.5) that incorporates unobserved heterogeneity to check that results without it are not biased. For this purpose, we follow Meyer (1990) and specify unobserved heterogeneity across individuals by assuming that, if this is present, it is independent of the covariates in x, that its distribution has a gamma mixture, and that it enters the hazard function multiplicatively. Hence, we define Ω_i as the random variable for each individual, i, and specify the hazard function as:

$$h_{um}(t_{um}) = h_{0m}(t)\exp(\beta' x)\Omega_i \qquad (j = 1, ..., M;\ \ j \neq u) \qquad (1.6)$$

◇ Co-variates

The vector x in (1.5) of explanatory variables for the estimation of ith individual's hazard rate is constituted by a set of dummy variables. The dummy variables equal one if a requirement is fulfilled, and zero, otherwise.

These sets of variables which have already been discussed in section 1.4. in our comments to table 2, are the following ones: four dummies for age group (23 to 28, 29 to 35, 36 to 44 and 45 to 65 years old); three for education (secondary school, high school, and more than high school); two for civil status (married with children under 18, married with children over 18, or with no children); one for another member of the household working; four for search method (if the job was located through an advertisement on the Internet, on radio, or in a newspaper, whether family or friends were asked to recommend a job or to keep them informed about any job possibilities, if the job was offered to them, or if they went to an employment agency); three for previous job status combined with their reason for leaving their previous employment (formal and left voluntarily, formal and laid off, or informal and laid off), one for an urban area; one if they received a payment associated with separation from their previous job, two that capture year effects (2006 and 2007) and finally, 31 dummy variables are included to control for geographic regional differences (Mexican states). As mentioned in the last paragraph, the previous length of unemployment reported by the individual on the day of his first interview, must be included as an explanatory co-variate. In our preferred specification, three dummy variables capturing time already spent in unemployment, are incorporated in the estimated hazard function. These were: more than one month, but less than two; between two and four months, and more than four months.

The omitted variables in the estimation of hazard functions are: age group between 18 to 22 years old, less than secondary school, single, no other member of the household working, directly contacted the business establishment to search for a job, previous job was informal and left it voluntarily, located in a rural area, received no payment associated with separation from previous job, less than a month in unemployment, interviewed in 2005, and located in the capital of the country.

1.6. Results

1.6.1. *Determinants of job search duration*

Tables 4 and 5 report results for hazard functions corresponding, respectively, to specifications in (1.5) assuming no unobserved heterogeneity and (1.6) assuming heterogeneity exists, and for different job status destinations. They report hazard ratios for co-variates determining escape rates from unemployment to formal and informal salaried jobs, to self employment, and out of the labor force. None of the signs in hazard ratios in table

4 differ from the corresponding ones in table 5. The value of their corresponding parameters do not differ significantly, either. This suggests that unobserved individual heterogeneity is not an important source of bias, and we, therefore, concentrate the following analysis in results reported in table four.

Table 4
Hazard functions for unemployed male workers
(Cox Proportional Model)
(Time of unemployment after first interview in days)

Variable	*Transition rates from unemployment to:*			
	Formal job	*Informal salaried job*	*Self-employment*	*Out of labor force*
Age				
23 to 28 years old	1.1221 [.0778]*	.9899 [.0514]	1.9350 [.4527]***	.6550 [.0681]***
29 to 35 years old	1.0788 [.0860]	.9351 [.0524]	2.0554 [.4930]***	.5951 [.0892]***
36 to 44 years old	.9544 [.0877]	.8849 [.0531]**	2.6592 [.6338]***	.5303 [.0838]***
45 to 65 years old	.6967 [.0709]***	.7509 [.0461]***	2.3858 [.5982]***	.9296 [.1325]
Education				
Secondary school	1.4742 [.1107]***	.8344 [.0330]***	1.1990 [.1706]	.9978 [.1176]
High school	1.5120 [.1282]***	.6536 [.0388]***	1.2440 [.2245]	1.0237 [.1199]
More than high school	1.2166 [.1083]**	.4559 [.0318]***	1.3240 [.2150]*	.8981 [.0967]
Civil status				
Married or head of household & children under 18	1.3244 [.0968]***	1.2771 [.0638]***	3.1429 [.5613]***	.7242 [.1033]**

Table 4
(continued)

Variable	*Transition rates from unemployment to:*			
	Formal job	*Informal salaried job*	*Self-employment*	*Out of labor force*
Married or head of household without children or children older than 18	1.2508 [.0895]***	1.1554 [.0598]***	2.2905 [.4228]***	.9940 [.1226]
Worker in the household				
	1.0595 [.0599]	.9922 [.0354]	.7298 [.0814]***	1.1119 [.0962]
Search Method				
By newspaper, radio or internet	3.2566 [.2370]***	1.3057 [.1096]***		
By family or friends	2.3504 [.1510]***	2.4380 [.1067]***		
They offered you a job	1.1648 [.1672]	2.7228 [.1413]***		
Gov. emp. service, private emp. agency and others	1.1023 [.1851]	.6405 [.1135]**		
Previous job status and reason why he left it				
Previous job was formal and left his previous job voluntary	1.9075 [.1160]***	.7214 [.0458]***	.8322 [.1332]	.6229 [.0660]***
Previos job was informal and lay off	.5231 [.0494]***	1.3534 [.0506]***	.7082 [.0986]**	.6194 [.0675]***
Previous job was formal and lay off	1.7946 [.1187]***	.7613 [.0507]***	.7383 [.1252]*	.2596 [.0466]***
Urban area				
	1.3761 [.1004]***	.8178 [.0293]***	1.1270 [.1491]	1.1578 [.1339]

Table 4
(continued)

Variable	*Transition rates from unemployment to:*			
	Formal job	*Informal salaried job*	*Self-employment*	*Out of labor force*
Lump-sum job separation payment				
	.7090	.6747	.7210	1.8150
	[.0942]***	[.0846]***	[.1761]	[.2348]***
Previous lenght of unemployment				
More than 30 to 60 days	.8342	.6348	.6383	1.1137
	[.0652]**	[.0437]***	[.1088]***	[.0950]
More than 60 to 120 days	.6628	.6819	.3735	1.0972
	[.0685]***	[.0578]***	[.0948]***	[.1096]
More than 120 days	.5386	.4638	.4237	.9631
	[.0717]***	[.0581]***	[.1252]***	[.1119]
Year control				
Year (2006=1)	1.1637	1.0343	.9883	.8224
	[.0702]**	[.0416]	[.1294]	[.0728]**
Year (2007=1)	1.0065	.9822	.9507	1.1312
	[.0614]	[.0396]	[.1235]	[.0933]
Controls for Mexican state effects (31 dummy variables)				
Observations	6322	6322	6322	6322

Notes: Standard errors are in parentheses. One, two and three asterisks indicate significance at the 10%, 5% and 1% significance level respectively. Reference category: age group between 18 to 22 years old, less than secondary school, single, no other member of the household working, attended directly to the establishment to search for a job, previous job informal and left it voluntarily, located in rural area, received no payment associated to separation from previous job, less than a month in unemployment, interviewed in 2005 and located in the capital of the country.

◇ Time dependency and hazard rates

Hazard rates to formal or informal salaried jobs, or to self employment as implied by figures in rows 20-22 of columns 1, 2, and 3 of table 4, indicate that the longer an individual searches for a job, the lower their hazard rates out of unemployment are. These results suggest that workers' and employers' behavior change as the length of the unemployment spell of the worker increases. This could be either because search intensity of workers decrease with the length of unemployment, or because job offers arrive less frequently, the longer a worker is unemployed (*e.g.* because employers take the view that too long a period of unemployment sends a bad "signal", or because their productive ability effectively declines). This also highlights the usefulness of timely interventions before individuals become unemployed on a longterm basis.

Table 5
Hazard functions for unemployed male workers
(Cox model with unobservable heterogeneity)
(Time of unemployment after interview in days)

Variable	*Hazard ratios*		
	Formal	*Informal*	*Out of labor force*
Age			
23 to 28 years old	1.2144 [.1444]	.8656 [.0721]*	.5400 [.0996]***
29 to 35 years old	1.1173 [.1521]	.8179 [.0779]**	.5226 [.1175]***
36 to 44 years old	.9058 [.1345]	.7365 [.0759]***	.8317 [.2027]
45 to 65 years old	.6566 [.1044]***	.5635 [.0627]***	4.0602 [1.1134]***
Education			
Secondary school	1.9767 [.2467]***	.5642 [.0448]***	1.2407 [.2287]
High school	2.1535 [.3026]***	.4398 [.0440]***	2.2930 [.5134]***

Table 5
(continued)

Variable	*Hazard ratios*		
	Formal	*Informal*	*Out of labor force*
More than high school	1.7434 [.2418]***	.3204 [.0340]***	2.2075 [.4809]***
Civil status			
Married or head of household and children under 18	1.3800 [.1656]***	1.3925 [.1170]***	.1207 [.0354]***
Married or head of household without children or children older than 18	1.3177 [.1586]**	1.1134 [.0921]	.3123 [.0710]***
Worker in the household			
	1.1706 [.1093]*	.9619 [.0594]	1.2460 [.1840]
Search method			
By newspaper, radio or internet	7.4060 [1.7990]***	1.2689 [.1328]**	
By family or friends	2.7572 [.3252]***	3.8636 [.3753]***	
They offered you a job	.9533 [.1710]	9.1609 [1.8887]***	
Gov. emp. service, private emp. agency and others	1.2089 [.2692]	.7234 [.1390]*	
Previous job status and reason why he left it			
Previous job was formal and left his previous job voluntary	3.2202 [.5182]***	.4863 [.0438]***	.3427 [.0734]***
Previos job was informal and lay off	.4035 [.0508]***	1.9553 [.1596]***	.2809 [.0634]***
Previous job was formal and lay off	2.8894 [.4383]***	.5749 [.0530]***	.0988 [.0339]***

Table 5
(continued)

Variable	*Hazard ratios*		
	Formal	*Informal*	*Out of labor force*
Urban area			
	1.7162	.6016	1.4231
	[.1923]***	[.0432]***	[.2312]**
Lump-sum job separation payment			
	.6017	.6476	8.3758
	[.1229]**	[.1056]***	[3.1015]***
Previous lenght of unemployment			
More than 30 to 60 days	.7691	.5912	4.0450
	[.0922]**	[.0521]***	[1.0397]***
More than 60 to 120 days	.5629	.6837	3.6436
	[.0896]***	[.0738]***	[.9590]***
More than 120 days	.4266	.4592	3.7826
	[.0896]***	[.0697]***	[1.1276]***
Year control			
Year (2006=1)	1.1802	.9787	.9216
	[.1146]*	[.0655]	[.1372]
Year (2007=1)	.9613	.8651	1.4334
	[.0958]	[.0594]**	[.2297]**
Controls for Mexican state effects (31 dummy variables)	x	x	x
Unobservable heterogeneity	.6374	-.7274	1.3996
	[.2865]**	[.2990]**	[.3677]***
Observations	6322	6322	6322

Standard errors in parentheses. One, two and three asterisks indicate significance at the 10%, 5% and 1% significance level. Reference category: age group between 18 to 22 years old, less than secondary school, single, no other member of the household working, attended directly to the establishment to search for a job, previous job informal and left it voluntarily, located in rural area, received no payment associate located in rural area, received no payment associated to separation from previous job, less than a month in unemployment, interviewed in 2005 and located in the capital of the country.

A comparison of the results in tables 4 and 5 indicates that a negative time duration prevails when unobserved heterogeneity is incorporated as part of the specification. That is, after comparing the figures obtained when estimations are based on the model in (1.6) (which incorporates unobserved sources of heterogeneity that are not readily captured by covariates in x) with those obtain in (1.5) (which does not incorporate them), we reject the hypothesis that negative time duration is attributed to unobserved heterogeneity biasing specification results, and we cannot reject the hypothesis positing that it is attributed to negative duration dependence at the individual level.[13]

Instead of capturing the effect of the co-variate, "previous length unemployment", by a set of co-variate dummy variables, table 6 presents an alternative estimation. This one captures it with a variable representing, "length in unemployment", in units of two weeks, it's squared value, and it's value to the third power. Results were not substantially different than those in table four.

◇ Hazard rates and the economic cycle

These results are consistent with the contention that during years in which GDP growth accelerates, formal job offers arrive faster to unemployed workers.[14] The last two rows of the first column of table 4 imply that the workers' escape rate from unemployment to formal jobs was 16% higher in 2006 than in 2005 and 2007.[15]

Conversely, the results in the fourth column of table 5 state that, during periods of economic expansion, individuals search longer before opting out of the labor market as is apparent in the last two rows of the third column

[13] Because we work with 'mixed proportional hazard' specifications –also called Cox proportional hazards– there is a baseline hazard, $h_0(t)$, which captures the common hazard among individuals in the population. It is, therefore, possible to graph, as in Tansei and Tasci (2004), the baseline hazards evaluated at the means of the co-variates for specification (1.5) and (1.6), and assess differences in changes in the probability of finding a job as the time changes. This is another possible source of duration dependence that is not considered here because of the relatively short duration captured by the common hazard (It is not longer than three months in these estimations).

[14] As shown in graph 1, relative to corresponding rates in 2005 and 2007 –which are the years with slow growth– the average of GDP growth rates during the first two quarters of 2006 are almost twice as high.

[15] Results also indicate that exit rates to informal employment and self-employment are not statistically significantly related to the dummy variables representing years with different rates of growth of GDP.

of table 4. In years of slow economic growth, unemployed individuals go faster to the non-participation state (the counterpart of high hazard rates to the non-participation state are longer spells of job searching).

The results associated with exits to formal employment suggest that public funding to active labor market intermediation in this segment of the market should be countercyclical: as the economy slows down, more time is required by individuals to find a formal job which offers them an acceptable wage. A related remark is valid for individuals opting out of the labor force: net gains for potential participants in training programs targeted at the unemployed are larger, since opportunity costs for individuals to be in the labor market during the downswing phase of the cycle, are lower.

Table 6

Hazard functions for unemployed male workers with previous job experience (Cox Proportional Model)

(Time of unemployment after first interview in two week periods)

Variable	*Transition rates from unemployment to:*			
	Formal	*Informal*	*Self-employment*	*Out of labor force*
Age				
23 to 28 years old	1.1154	.9872	1.9534	.7480
	[.0724]***	[.0458]***	[.4554]***	[.0601]***
29 to 35 years old	1.0865	.9615	2.1330	.7064
	[.0819]	[.0470]	[.5069]***	[.0844]***
36 to 44 years old	.9598	.9233	2.8016	.6689
	[.0835]	[.0486]	[.6608]***	[.0860]***
45 to 65 years old	.7243	.7868	2.6008	1.1059
	[.0702]***	[.0422]***	[.6449]***	[.1271]
Education				
Secondary school	1.5100	.8466	1.2195	.9296
	[.1080]***	[.0287]***	[.1707]	[.0794]
High school	1.5224	.6712	1.2928	1.0404
	[.1215]***	[.0361]***	[.2310]	[.0892]
More than high school	1.2640	.4840	1.4526	.8826
	[.1075]***	[.0316]***	[.2333]**	[.0706]

Table 6
(continued)

Variable	*Transition rates from unemployment to:*			
	Formal	*Informal*	*Self-employment*	*Out of labor force*
Civil status				
Married or head of household and children under 18	1.2459 [.0867]***	1.1952 [.0525]***	2.7487 [.4892]***	.6192 [.0702]***
Married or head of household without children or children older than 18	1.1998 [.0823]***	1.0992 [.0503]**	2.0989 [.3828]***	.8328 [.0803]*
Worker in the household				
	1.0652 [.0565]	.9833 [.0304]	.7433 [.0824]***	1.0907 [.0756]
Search Method				
By newspaper, radio or internet	3.0628 [.2097]***	1.2416 [.0979]***		
By family or friends	2.1973 [.1350]***	2.2565 [.0899]***		
They offered you a job	1.0669 [.1491]	2.4757 [.1107]***		
Gov. emp. serv., private emp. agency and others	1.1026 [.1769]	.6620 [.1139]**		
Previous job status and reason why he left it				
Previous job was formal	1.8450 [.1068]***	.6939 [.0412]***	.7834 [.1233]	.6751 [.0583]***
Lay off	.5110 [.0479]***	1.2902 [.0424]***	.6707 [.0927]***	.6229 [.0573]***
Previous job was formal and lay off	1.7771 [.1110]***	.7388 [.0466]***	.7254 [.1221]*	.2800 [.0462]***
Urban area				
	1.3972 [.0979]***	.8416 [.0255]***	1.1512 [.1501]	.9493 [.0816]

Table 6
(continued)

Variable	*Transition rates from unemployment to:*			
	Formal	*Informal*	*Self-employment*	*Out of labor force*
Lump-sum job separation payment				
	.6994	.6969	.7748	1.6878
	[.0881]***	[.0814]***	[.1864]	[.1469]***
Previous lenght of unemployment				
In two weeks period	.9294	.8349	.6998	1.0860
	[.0391]*	[.0293]***	[.0694]***	[.0400]**
In two weeks period	1.0026	1.0110	1.0238	.9924
	[.0052]	[.0044]**	[.0121]**	[.0040]*
In two weeks period	1.0000	.9998	.9996	1.0002
	[.0002]	[.0001]	[.0003]	[.0001]
Year control				
Year (2006=1)	1.1444	1.0034	.9641	.9571
	[.0654]**	[.0356]	[.1242]	[.0641]
Year (2007=1)	1.0079	.9471	.9262	1.1343
	[.0585]	[.0338]	[.1196]	[.0721]**
Controls for Mexican state effects (31 dummy variables)				
Observations	6322	6322	6322	6322

Notes: Standard errors in parentheses. One, two and three asterisks indicate significance at the 10%, 5% and 1% significance level.

◇ Hazard rates and search methods

Individuals searching for a formal job *via* newspapers, radio and the Internet escape unemployment faster than those relying on their social and family networks. It is not surprising that these two search methods are relatively more efficient than attending to establishments directly (factory, shop, plant, etc.). However, it is surprising that these methods are relatively more efficient than searching for job via government employment services, via governmental programs of temporary jobs, or through private employment agencies. This result suggests that, in Mexico, these intermediation services must be subject to revision and improvement. They might help individuals to find a job, but not to find one faster.[16]

In turn, as expected (Calvó Armengol and Ioannides 2005), those relying on family and social networks to be informally employed escape unemployment faster that those having to search via different methods.

◇ Age, education and hazard rates

As shown in the fourth row of columns 1 and 2, relative to younger persons, individuals take longer to find a salaried job -formal or informal- when their age is between 44 and 65 years old.[17] These results suggest the need for programs that help individuals over 44 years old to find a job. By contrast, relative to the rest, individuals over 36 years old spend less time in unemployment before starting to work as self-employed, suggesting work experience is an advantage in this job status. In turn, the fourth column of table 4 indicates that the first ones to get discouraged about the possibility of finding an acceptable job are youngsters under 23 years old and senior workers over 44.

Regarding the results on how education levels affect unemployment duration according to different job status destinations, those in the fifth row of columns 1 and 2 of table 4 show that individuals with less than a secondary education (corresponding to the omitted dummy variable in the estimated hazard functions) become informal employees faster than more educated unemployed workers. Conversely, relative to the rest, individuals with low education levels require longer job search spells for formal jobs.

It is possible to suggest two reasons for these results. One is that most firms requiring workers with low skill levels self-select into the informal sector, hence, relative to the formal sector, job offer arrival rates are higher for them in the informal sector. The other one is that workers with less education might be less willing or less likely than more educated workers, to afford paying the benefits associated with formality. Therefore, their acceptance probability of jobs in the formal sector is lower. These two

[16] A different interpretation is also possible, namely that the result is not because of the efficiency of the search method, but because of a self-selection of this method by individuals with low potential productivity.

[17] A distinguished feature of Mexican labor legislation may jeopardize these age groups' prospects of exiting unemployment to a formal job. This is that, once in a job, there is no age for compulsory retirement. Hence, potential employers consider that if laid off, they have to be indemnized.

reasons originate from the following problem: in economies with high non-wage costs of formal jobs, as is the case with the Mexican economy, formal employers will be willing to incur these costs if they are able to transfer them to their workers in the form of lower salaries. Workers with less education might be less willing or less likely than more educated workers, to afford paying the benefits associated with formality: at low levels of income, their discount rates are so high that the perceived benefits do not match the cost of giving up actual levels of consumption.

◇ Signalling

In contrast to what happens in the search for informal jobs, workers who left their previous jobs voluntary, become formal employees faster than workers who left them involuntarily. This suggests that job dismissals do not constitute an adverse signalling in informal jobs, whereas, for formal jobs, they do. They might suggest to potential employers that, relative to workers who voluntarily left their previous job, their productivity is lower, as posited by the work of Canziani and Petongolo 2001, referred to in the theoretical review section of this paper.

◇ Escaping to formal jobs

Regarding determinants of duration in unemployment for those that find a formal job, from the first column of table 4, it is possible to infer profiles of individuals requiring the shortest searching time. These are individuals who are located in urban areas and enter unemployment for a reason other than being laid off, who were formal workers in their last job, younger than 44 years old, with a secondary education or higher and that contact their new employer *via* newspaper, radio or the Internet. In addition, it also states that, relative to single workers, married ones with children cannot afford to look as long for a suitable job and that, alternatively, the latter receive more wage offers.

Finally, as follows from row 18, when a person with these characteristics has no resources (provided by a lump-sum payment for job separation from his previous employment), he is employed faster. This is because, relative to those that count with a "financial cushion" to finance their job search, they cannot look so long for a job with desired characteristics.

◇ Escaping to self-employment

Becoming self-employed requires financial capital and job experience. This could explain why, in the third column of table 4, young unemployed individuals take longer to become self employed, and why human capital, captured by education levels and by being between 23 and 44 years old, helps them find a job faster.

An interesting result is related to the statistical significance of the variable of the individuals who are not the only person in the household earning an income. If another member of the household works, as well, individuals take longer to exit from unemployment to self-employment.

◇ Escaping to non-participation

Figures in table 1 indicate that a non-negligible percentage of job seekers opt out of the labor market in Mexico, and that this percentage is larger for those whose previous employment was informal. This stylized fact has been previously pointed out –for Mexico and other Latin-American countries– Duryea *et al.* (2006). These authors estimated determinants of the likelihood of these transitions. Our approach differs from theirs in that it estimates, instead, how long it takes for those in unemployment to become discouraged about finding a job; our results allow us to state that workers whose previous job was informal, search for a shorter period before moving out of the labor force, and to quantify how much longer a worker with previously formal job experience will persist in his search for a job.

1.6.2. *Escaping to informal salaried jobs and the controversy of labor market segmentation*

In the previous subsection we highlighted a difference in behavior between two groups of homogenous individuals that only differed in their previous job status. This was regarding their persistence in searching for an acceptable job before moving out of the labor force: relative to those whose previous experience was in an informal job, individuals whose job experience before transiting to unemployment was in the formal sector, search for jobs for a longer time before moving out of the labor force. Why would the former opt out to non-participation in the labor force sooner than the latter? One answer to this question is that those with better employment stories have higher expectations of receiving an acceptable job offer because they signal to prospective employers a higher potential productivity.

If this is the correct answer, another implication of signalling to prospective employers a higher potential productivity with their employment story, would be that a previously formal worker is expected to exit unemployment faster than a similar worker whose previous job was informal. Our results indicate that, controlling for other determinants of unemployment duration, this is indeed the case regarding hazards out to formal employment, but not out to informal salaried jobs.[18]

The figures in rows corresponding to previous job status in columns 1 and 2 in table 4 indicate: *a*) that relative to those who were previously formal, those that had had an informal job status require longer search periods to find a formal job; *b*) that those who were formal workers in their last job require more time to find an informal job than individuals with similar characteristics, but that were informal in their last job. That is, relative to those that remain informal workers, those changing from formal to informal job status took longer to find their job. Why would a previously formal worker take longer to find an informal job than an individual with the same observed characteristics except that he was an informal employee before entering unemployment?[19]

◇ Unsegmented labor markets

A first hypothesis of why this occurs follows the lines of reasoning implicit in frameworks suggesting integrated formal and informal labor markets: workers voluntarily shifted their job status, which implies that a compensating wage premium above formal wages was offered to them. They might take longer to find a job because their knowledge of informal labor market conditions is not as good as that of workers with previous informal jobs, but they improve their income relative to staying formal.

A test of the *hypothesis* of the existence of a wage premium for moving from the formal to the informal sector after an unemployment spell requires comparing earnings obtained by individuals accepting informal jobs, with hypothetical earnings that each of them would have obtained, had they worked, instead, in a formal job. A counterfactual estimation of earnings, based on Kernel matching methods, allows us to fulfill this requirement. Hence, we use this method to obtain a group of individuals with statistically similar observable characteristics that shifted job status after their

[18] This is controlling for the effect of two variables that would imply that these individuals escape unemployment faster to informal jobs: search method (informal workers that search for informal employment are more likely to rely on social and family networks) and 'lump sum payments from previous job separation' (the majority of previously informal workers are without this type of 'financial cushion' to smooth their consumption and to search for an adequate job match).

[19] An alternative answer is that the effect of work experience might be different and could depend on the sector in which the worker has been occupied (Woltermann, 2004). That is, while formal job experience is required for formal jobs, informal job experience is prefered for informal jobs.

unemployment spell, comparing them to the set of workers that also experienced an unemployment spell, but were formal in both their previous and their new jobs. We call it the control group. The counterfactual estimates of what workers in the group that switched status after unemployment, would have earned, if they had remained formal, were obtained from the control group using the matching method.[20]

Table 7 presents the workers' average hourly earnings in their new job, relative to their level in their previous job. The first column corresponds to counterfactual earnings, which, in turn, were those of the control group obtained with the matching method.

The second column corresponds to those belonging to the group of unemployed workers that were formal workers and became informal employees.[21] A statistical test of the discrepancy in the mean of these two groups' earnings, rejects the hypothesis of a wage premium obtained by moving from the formal to the informal sector after an unemployment spell. Based on these results, we conclude that, as opposed to what happens with workers with similar characteristics that, after their unemployment spell, remain formal, individuals that were formal in their previous jobs, are not better off in terms of salary if their new job status is informal employment.

◇ Segmented labor markets

An employment history in the formal sector signals to prospective employers a higher potential productivity than one in the informal sector signals. One would, therefore, expect that an informal job would be found faster by an individual that was a formal worker before entering unemployment, than by another one with the same observed characteristics except that his previous job was in the informal sector. Our results show that this is not the case: rows 15 and 17 of table 4 show that it takes longer to find an informal job for an individual that was a formal worker before entering unemployment, than for another one with the same observed characteristics except that his previous job status was informal. An explanation is that the informal sector was not the first choice for this set of workers whose previous job was formal, but they ended up working as informal employees never-the-less.

They spent time searching for a formal job, but got no acceptable offers from employers in this sector; after a time threshold –dependent

[20] The specification of the kernel matching methods, and the assumptions required for their applications are relegated to the appendix.

[21] Because the size of the former group resulted smaller than the size of the latter one, the matching method was applied with replacement, to pair each member of the switcher group with a member of the comparison group with similar observable characteristics.

on availability of resources to finance their job search– they looked for an informal job. That is, since they failed to receive acceptable offers from employers in the formal sector, their search intensity for a formal job decreased, and they concentrated their search efforts in getting an informal job.[22] In terms of the elements of the job search model referred to in section 1.2., in the first months of unemployment, the main element at work is the increase of the probability of acceptance, given a decreasing pattern of reservation wages. But as soon as this phase passes, the only element present in the hazard rate of escaping to the formal sector is the offer arrival rate, because acceptance probabilities are, in fact, equal to one. We posit that the lack of formal job offers arriving to these individuals reflects labor market segmentation.

Table 7

Unemployed male workers with previous working experience in the formal sector
Earning variations of switchers from formal to informal jobs

Year	*KERNEL Matching Method*				
	Counter- factual result Formal-Formal	*Registered result Formal-Informal*	*Difference*	*S.E.*	*T-stat*
	Hourly earnings relative to previous job				
2005	1.06	.89	.16***	.0451	3.66
2006	1.06	.91	.15***	.0410	3.56
2007	1.07	.96	.11***	.0458	2.43

A more complete information set about search behavior would be required to further substantiate this hypothesis. This would require employment surveys to capture if workers search simultaneously for formal and

[22] A similar explanation could be suggested for young unemployed individuals that become self-employed: relative to older workers with more working experience, it takes them longer to become self-employed because this job status was not their preferred option. They initially spent time looking for salaried employment.

informal jobs, or if do they do so sequentially;[23] if it is the case that their search is sequential, is it after becoming discouraged with the prospect of achieving their preferred job status, that previously formal workers start searching for an informal job?

1.7. Concluding Remarks

A stylized fact of the Mexico's labor market dynamics is that a significant share of unemployed individuals that found a job as informal employees, were formal workers in their previous employment spell. Estimates of their counterfactual earnings in formal jobs indicate that their wages would have been higher if they had found a job there. Based on these results, for those in this subset during the first semesters of 2005, 2006 and 2007, we argued that these kind of switches between job sectors are not consistent with the *hypotheses* implying voluntary movements in response to higher wages offered in the informal sector. A comparison of the longer lengths of time previously formal employees took to become informal employees. compared to similar individuals who previously held jobs in the informal sector, also indicates that the informal sector was not their preferred option.

We substantiated the hypothesis of an informal job as a non preferred option for unemployed workers who previously held formal jobs –and its implications for the labor market segmentation controversy– with an application of time-to-event statistical methods to employment survey data sets applied quarterly in Mexico since 2005. With these methods, we identified that unemployed individuals who previously held formal jobs require longer searching spells and efforts to get a job in the informal sector, relative to those with previous informal employment. This is controlling for effects attributed to social networks and other search methods, for financial resources provided by previous job separation, for regional and year effects, and for other determinants of individual duration in unemployment.

The result is consistent with the contention that, after a period of job searching and, in spite of lowering their reservation wages, a subset of formal workers that become unemployed, fails to obtain acceptable job offers which would permit them to remain in their preferred job status. After this initial phase of unsuccessful searching for a formal job, they concentrate their search efforts in the informal segment of the market where

[23] One would like to have answers to the question: given that your new job is an informal employee, did you also search for a formal job? If so, for how long? With this additional information, a multi-spell variation of a hazard function could be applied, as in Van den Berg (2001). In this framework, searching for a formal job and searching for an informal job can be estimated as different spells that ocurr one after the other.

they end up obtaining job payments that lack the benefits associated with being a formal worker, nor do they receive compensation for this lack of benefits.

Among the main factors that an analytical model, aiming to explain this process, should have are the following: market frictions in the formal segment of the labor market,[24] the increasing costs, as time lapses, of searching for formal jobs, with the impossibility of financing such searches due to credit market imperfections, low levels of precautionary savings, and expectations that informal job offers arrive relatively more frequently. Another factor that could complement the analytical explanation is that workers might consider the informal job as a temporary one with short expected duration. That is, that given evidence of considerable mobility between informal and formal jobs in Mexico (Calderon-Madrid, 2000), workers might have expectations of receiving a formal job offer while working as an informal employee, or during their next unemployment episode.

This has an important implication for public policy design for formal workers. This is that active labor market policies must not only shield employees from labor market malfunctioning resulting in the risk of prolonged unemployment, but also from the risk of being involuntarily displaced to a low income job without the benefits associated with being a formal worker. Another implication for the design of active labor market programs derived from this study is that public funding for active labor market programs in the formal segment of the market, such as training programs targeted at the unemployed, should be countercyclical. We show that, as the economy slows down, more time is required by individuals to find a formal job, and their opportunity cost of being out of a job in that phase of the cycle is lower[25]. We also demonstrated that the longer an individual searches for a job in the Mexican labor market, the lower their hazard rates out of unemployment, a result suggesting that workers' and employers' behavior changes over time, which highlights the usefulness of timely interventions before individuals become unemployed long-term.

In turn, our study points out that searches for employment in Mexico via government employment services, a public program for temporary jobs, or a private employment agency, might help individuals find a job, but don't help them find it faster than is the case via other methods: we found that individuals escape unemployment faster searching for a formal job via newspapers, radio and the Internet, and for informal employment, via social and family networks. This suggests a need for the revision of these kinds of publicly sponsored intermediation activities.

[24] Zenou (2008), for example, introduce a urn-ball and coordination failures.

[25] A related remark is valid for workers opting out of the labor force when the economy slows down.

We also assessed what happened with previously informal workers who, after an unemployment spell, became formal employees. We found that they require longer searching spells and efforts to get an acceptable job offer in the formal sector relative to those with the same observed characteristics, but with previous formal job experience. This result suggests that recent job experience within a job status might be a signaling device to employers in the formal sector of the quality of an employee's skills. In terms of feedback for program design, it indicates that entrance prospects into the formal sector for workers without formal job experience might be jeopardized by malfunctioning of the labor markets due to information asymmetry problems, and not only by the kind of barriers to entry which are commonly put forth to explain labor market segmentation. Hence, the corollary is that programs targeting the unemployed with no previous formal job experience, will increase their effectiveness when accompanied with assessment and certification of labor competency granted by institutions who have credibility with potential employers.

Last, but not least, this result also has implications for labor legislation reforms: strict employment protection regulations in Mexico might be aggravating problems originating from asymmetric information in labor markets. When employment protection regulations increase the shadow cost of hiring workers in an environment with asymmetric information, there might be more reluctance by employers to hire workers with no formal job experience. In the context of a firm's limited knowledge of the productivity of workers, employers take into consideration the fact that they may want to dismiss them in the future, thereby undergoing costly firing procedures. Because of this, relative to another worker with equal observed characteristics, but coming from a previous informal job, employers would hire those that signal their potential skills with previous formal job experience.

Appendix

To construct the required counterfactual earnings in the formal sector of workers that, after unemployment, move from formal to informal jobs, we followed a matching procedure similar to the one in Pratap and Quintin (2006). As in the research of these authors, earnings of employees that changed job status are compared with their counterfactual outcome, had they stayed in the same job status. For this purpose, movers from a job status are paired with stayers in that status that have similar characteristics, applying propensity score matching methods.[26]

In view of the large number of pre-treatment observable characteristics, we applied the propensity score method variant of matching (Rosenbaum and Rubin, 1983). This variant has the advantage of reducing the dimensionality of the matching problem down to matching on one scalar, while considering the importance of all pretreatment variables included in the analysis. This scalar is the propensity score, $P(W)$, defined as the probability of switching from the formal to informal job status after unemployment, conditional on observable characteristics. We incorporated as predictor variables in a logit regression the following: the reason the previous job was left, geographic zones where the individual was located; three categories of family status, civil status; characteristics of their previous job: part- or full-time, formal or informal sector, whether the individual was a wage earner or self-employed; age; nine categories of education, and ten of occupation in their previous job.[27]

◇ Counterfactual estimation of earnings in formal jobs of individuals that end up in informal jobs

Let T be the set of workers moving out of a job status, C, the set of individuals remaining in that status. In turn, Y_i^T and Y_i^C are defined, respectively, as the observed earnings of preivously formal workers moving, after an unemployment spell, from the informal sector, and of those that were also formal but finding a formal job, after their unemployment spell. The average discrepancy in earnings between formal and informal jobs, τ, (formal sector premium) is given by the following relationship:

[26] This procedure to estimate counterfactual earning of workers is based on assumptions that are not fulfilled when individuals self-select into a job status on the basis of characteristics not observed by an analyst. For a specification of the statistical assumptions under which this procedure is based, *cfr.* Heckman, Tood and Ichimura, 1998.

[27] Logit results are not presented here, but are available upon request to the author.

$$\tau = E(Y^C|X, Z, sector = 1) - E(Y^T|X, Z, sector = 1) \tag{1.7}$$

where X and Z denote individual and employer characteristics, respectively. We assumed the following conditional independence of Rosenbaum and Rubin (1983).

$$Y^T, Y^C \perp X, Z|sector \tag{1.8}$$

The previous condition implies that selection only take place on observables. Then the average treatment effect estimator is:

$$\tau = E(Y^C|X, Z, sector = 1) - E(Y^T|X, Z, sector = 0) \tag{1.9}$$

To estimate τ, we denote p_i the propensity score $P(Sector = 1|X_i, Y_i)$ of worker i given their vector (X_i, Y_i) of individual and employer characteristics. Rosenbaum and Rubin (1983) establish that if the conditional independence condition holds, and propensity scores are almost surely interior, conditioning on propensity score is equivalent to conditioning on the covariates themselves.

◇ The Kernel Matching Estimator

The kernel matching estimator of the average discrepancy in earnings of these sets, τ^K, is given by:

$$\tau^K = \frac{1}{N^T} \sum_{i \in T} \left\{ Y_i^T - \frac{\sum_{j \in C} Y_j^C G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \in C} G\left(\frac{p_k - p_i}{h_n}\right)} \right\} \tag{1.10}$$

where G is a kernel function, and h_n is a bandwidth parameter, and the number of units in the movers group is denoted by N^T. Under standard conditions on the bandwidth and kernel

$$\frac{\sum_{j \in C} Y_j^C G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \in C} G\left(\frac{p_k - p_i}{h_n}\right)} \tag{1.11}$$

is a consistent estimator of the counterfactual outcome we are interested in estimating. The standard errors for statistical testing are obtained by bootstrap.

Part 2

Programs for unemployed: Casual jobs or better and sustained jobs?

2.1. Introduction

Because of their precarious economic situation, unemployed workers without adequate job-related skills represent a major problem in developing countries. It is unlikely that they can increase their employability prospects without government help, partly due to market failures in labour and credit markets and partly due to their few resources and chances to find an employment with opportunity to 'learn on the job' within a supportive work environment.

The most common instruments available in developing countries to help them are publicly sponsored training programs of short duration. These are intended to be more than an income support mechanism for their beneficiaries. Their aim is to help individuals back to work and to help them achieve good job matches. A knowledge of their effectiveness in achieving this aim is a necessary feedback for policy makers to continue their funding or to modify the structure of the program. In spite of the importance of this feedback, evaluation studies dealing with the performance of this kind of programs in developing countries have not adequately dealt with their impact on beneficiaries' subsequent employment histories. Available studies have dealt exclusively with the program's impact on wages, on time to find a job and on the probability of finding one - and not on re-employment dynamics.[1] Moreover, the data sets used for these evaluations would not even lend themselves to measuring the programs' impact on re-employment dynamics of their beneficiaries. This is because the evaluation design did not consider applying, as part of their beneficiaries' surveys, questions that can capture longitudinal data covering employment spells after program participation. An exception is a data set collected in 1994 for an evaluation of a Mexican training program targeted at the unemployed. This one pro-

[1] Samaniego (2002), Betcherman, Olivas and Dar (2004) and Ibarrarán and Rosas (2008).

vides appropriate longitudinal data for representative samples of beneficiaries of the program and of eligible individuals that did not participate in it. For each one of them, the survey registered the length of unemployment episodes and the duration of subsequent employment. This paper uses this data set to estimate the program's impact on weeks needed by participants to find a job and on time spend in that job.

Our resuts show that the program has positive effects on post-training employment durations, effects that are ignored by evaluations that focus solely on escape rates of unemployment, re-employment wages or re-employment probabilities. We posit that benefits in yearly income earnings of participants attributed to improving their empoyability might be large enough to compensate the costs of the program. That is, that helping individuals find sustained employment that provides them the opportunity to 'learn on the job' and to increase their earnings by additional weeks worked in a year might justify costs of the program, even when post-training wages are not inmediately above their levels before joining the program.

The program's beneficiaries could register at one of five type of training institutions or receive training on-the-job at private firms. These institutions were administered through a network of state employment offices and differed in their organizational resources, in their capacity to identify and adapt their services to the requirements of the area in which they are located and in their degree of autonomy with respect to the central government. Because of these differences, the impact on re-employment dynamics of trainees is not expected to be the same at all places where individuals received their training. We show that this was the case by estimating corresponding impacts by geographic area and by the type of institution providing the training. We also investigate if some participants, with given characteristics, benefit more than others without them. We show that the program has heterogeneous effects according to their unemployment duration previous to training for male workers and for women according to the reason for leaving their previous job.

We also project the likely effectiveness of the program in different environments from the one where it was experienced. Based on estimated hazard functions, we predict the impact of the program beyond the sample framework. Finally, for cost-benefit analysis, we consider how the program achieves a reduction in forgone income.

The remainder of this paper is structured as follows. The program characteristics and its aims are discusses in section 2.2., with special emphasis on its objective of improving the employability of their beneficiaries. The data sets used for the evaluation are described in section 2.3., highlighting relevant information about re-employment dynamics and identifying modalities of the program and different institutions providing the services. The statistical framework used in this evaluation, namely multivariate multi-spell proportional hazard models, is presented in section 2.4. and results are discussed in section 2.5. How to predict the program impact beyond the sample framework is the subject of section 2.6., as well as what are the implications for cost-benefit analysis that can be derived from this work. The conclusions are in the final section.

2.2. The program and its aim

For years, the Mexican government has funded and administered a training program targeted at unemployed individuals with previous working eperience. This program, called PROBECAT (the Spanish acronym for *Programa de becas de capacitación para desempleados*) has been the government's most important active labor market policy to improve the productivity and employability of the unemployed. Although its name has been changed twice (in 2001 to SICAT, *Sistema de capacitación para el trabajo*, and in 2007 to BECATE, *Becas a la capacitación para el trabajo)*, its importance as an active labor market policy has remained the same.

The program was initially launched in the late 1980's and after a yearly registration of less than 50 000 persons up until 1992, it was expanded eightfold. It achieved a record level of 580 000 trainees in the year 2000. Its beneficiaries receive training, which lasts two to three months, at one of many training institutions nationwide or on-the-job at private firms. They also receive allowances equivalent to one minimum wage while enrolled in the program, plus transportation and partial health insurance coverage.[2]

Individuals targeted with this program are characterized by their risks of prolonged periods of inactivity and their propensity to find only casual and temporary employment. This is why improving their employability is a main pursuit of the program. To assess if this aim is achieved, a knowledge of the program's effectiveness in helping individuals find a 'sustained' job - as opposed to 'any job' is needed.[3] This in turn, requires, as a starting point for an evaluation, information about re-employment dynamics of trainees, such as the one represented in figure 1. This figure represents an hypothetical beneficiary of the program who was employed in a second post-training

[2] Other important features of the program are described in Revenga, Riboud and Tan (1994), STPS (1995) and Delahara, Freije and Soloaga (2008).

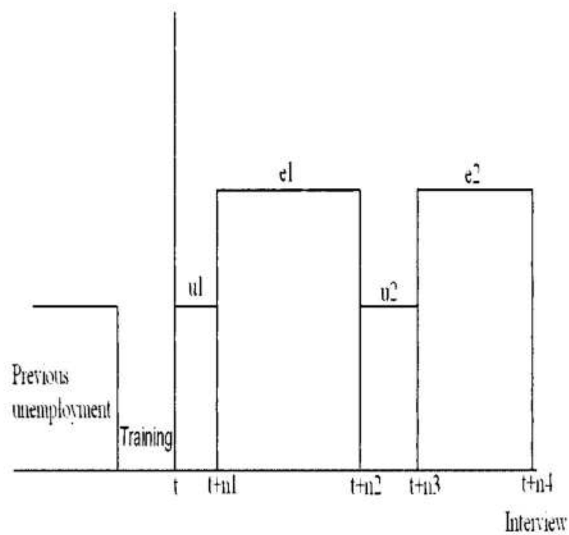
[3] In some developed countries and in developing ones during periods of severe economic recessions, the rationale of publicly funded training schemes is to offer a temporary refuge against unemployment to individuals with human capital to protect them against losses in it, until good times come.

job on the day in which he/she was interviewed. He experienced two unemployment spells between the end of the training (represented by point in time t) and the date of the interview (t+n4). The first unemployment spell, u1, had a duration of n1 weeks and the second one, u2, of n3-n2 weeks. He found an initial job, e1, left it after n2-n1 weeks, and at the time of the interview had been working in a second job for n4-n3 weeks. The figure also shows that, prior to joining the program, this person had already experienced a number of weeks of unemployment, information that is also provided by the surveys.

The lower part of figure 1 represents an hypothetical scenario of what would have happened with the individual represented in the upper part, if he had not participated. The case illustrated there is consistent with an effective program. In his counterfactual job history, the individual would have had only a casual job with duration given by the difference between t_1^* and t_1^{**}, which took him longer to found.

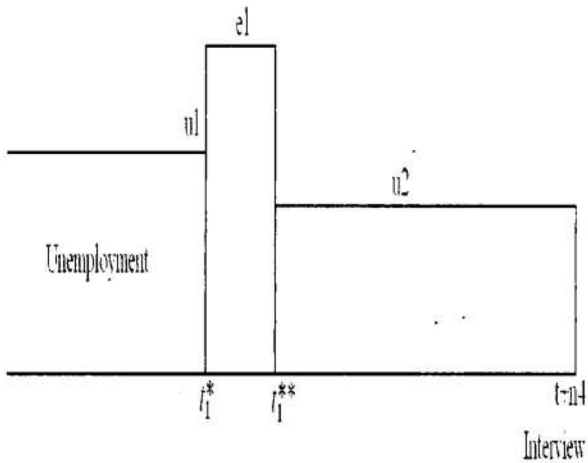
Figure 1

Re-employment dynamics of unemployed workers



a) Beneficiary of the training program

Figure 1
(continued)



b) Counterfactual case

A survey applied to trainees of the 1993 cohort of PROBECAT, and described in the following section, is the only one in existence that lends itself to measure their re-employment dynamics and to assess if the program is achieving its aim of improving the employability of the unemployed. It provides longitudinal data, for up to 18 months after their participation in the program, covering more than one episode of unemployment after the training of the respondent, as well as the duration of his/her employment spells.

◇ Modalities of the program

PROBECAT is financed by the Ministry of Labor and administered through a network of state employment offices. The training provided by this program is classified in two modalities. The first one, which we will henceforth refer to as school-based training, consists of formal courses and training offered in institutions associated with either the Ministries of Education and Labor or with private industry organizations. The second one, whom we will refer to as mixed training, consists of on-the job training in firms. In this modality the government pays the stipend, as well as related costs, while participating employers provide training and are required to hire at least 70% of trainees upon completion of the program.

◇ Institutions offering the program

The services of the school-based training modality are offered in official institutions associated with the Ministries of Education and Labor. The most important are the following four: CONALEP, CECATI, CETI, and CEBETI. CONALEP, *Colegio Nacional de Educación Profesional Técnica*, is a public decentralized body. Both CEBETI, *Centros de Bachillerato Tecnológico Industrial y de Servicios*, and CETI, *Centros de Ense ñanza Técnica Industrial*, are coordinated by the General Directorate of Technological and Industrial Education of the Ministry of Education. Finally, CECATI, *Centro de Educación para el Trabajo Industrial*, is operated by state governments. In addition to these, a number of private-sector training institutions, closely related to industry organizations, but regulated by the Ministry of Labor can also provide the services of PROBECAT.

2.3. Description of the data

The beneficiaries survey was applied to a representative sample of 1932 participants of the training program (1488 men and 444 women). A survey with the same questions was applied to an appropriate comparison group. This was integrated by individuals that did not participate in the program, but were elegible to do so. The answers of the members of this latter group are needed to infer counterfactual outcomes for participants. namely what the beneficiaries of the program would have experienced had they not participated.

2.3.1. *Beneficiaries group description and survivor rates of their members*

As shown in table 1, the majority of PROBECAT trainees in our sample participated in the school-based modality. Taking into consideration similarities in labor markets and geographic proximity, we divided the country into six zones. These are: the West; the North, excluding in-bond (*maquiladora*) regions: the coast: the in-bond region on the northern border of Mexico; the South: and central Mexico, including Mexico City. Table 1 presents the distribution of trainees of school-based modalities by zones. As it was the case with the rest of program beneficiaries and with the members of the comparison group, those trained in the school-based modality were asked why they left their last job before joining the program and the length of time between leaving that job and joining the program. The number of possible answers to these questions, whose distribution is presented in table 2, is four for the former question and five for the latter.

Table 1
Program participants

	Zone 1	*Zone 2*	*Zone 3*	*Zone 4*	*Zone 5*	*Zone 6*	Total
School Based Modality							
Male							
CONALEP	71	89	58	35	66	231	550
CONALEP	71	89	58	35	66	231	550
CECATI	73	68	109	28	21	39	338
CEBETI	38	14	70	7	26	6	161
PRIVATE	7	11	0	0	0	0	18
CETI	23	5	0	0	8	1	37
Other	26	47	81	6	54	72	286
Total	238	234	318	76	175	349	1390
Mixed modality	61	33	2			2	98
Female							
CONALEP	20	27	2		16	38	103
CECATI	52	7	15		8	0	82
CEBETI	14	8	24		0	0	46
PRIVATE	0	14	0		0	0	14
CETI	3	9	0		0	7	19
Other	8	1	5		32	12	58
Total	97	66	46		56	57	322
Mixed modality	69	46			7		122

Note: Zone 1: Western Region, Zone 2: Northern Region (excl. in-bond reg.), Zone 3: Coast of Mexico, Zone 4: In-bond region in Northern states, Zone 5: Southern States, and Zone 6: Mexico City and Central region.

◇ Survivor rates in employment and unemployment

In addition to the time between the end of program participation (march 1993) and the beginning of employment, the survey registered whether respondents were still in their first post-training job at the moment of the interview (September, 1994). If that was not the case, it registered the length of time during which they kept that job. In turn, for those trainees with more than one employment spell after training, the survey registered the length of time required to leave their second unemployment spell.

Data on the time spent in each job status by individuals who were trained in the school-based modality, revealed that, after finishing their training: a) 34% of male participants had already found a job within a month, b) one out of three of them was still unemployed by the end of the fourth month, c) one out four remained unemployed by the middle of the year, and d)12% of them spent more than 360 days unemployed.

This is shown in the first column of table 3,[4] which presents the proportion of men who remained unemployed after finishing their training. In turn, figures in the second column of table 3 indicate that, while 76% of them stayed in their job for at least four months, only two out of three men lasted longer than six months in their first post-training job, and only half of them stayed for at least one year. Finally, of those men who found employment but had left their first post-training job by the time of the interview, the following can be stated, based on the figures in the third column of table 3: at one extreme, 40% were already employed again within a month of loosing their job and, at the other extreme, 9% remained unemployed after a year.

In contrast, figures from the fourth and fifth columns show that the unemployment rates of the women with previous working experience who participated in the program were significantly higher during the periods examined. Barely half of these women had found a job within six months, and 32% remained unemployed a year after finishing the training. In addition, although employment retention rates for these women were similar in pattern to those of the men, the survival rates for each date were relatively lower for the women.

[4] This table enables us to visualize implied survival rates in unemployment by means of the so-called 'Kaplan Meir estimator'. This is an actuarial non-parametric estimator commonly used in the elaboration of life tables by demographers. It represents exits out of the unemployment state as a percentage of individuals "at risk". As part of this latter subset, it incorporates information provided by those that remain in unemployment at the time of their last interview and are identified as "right-hand censored data" (Kiefer, 1998).

Table 2
Participants in the School-based training modality
Individuals with prior working experience
Percentage of total

a) Classified according to reason for leaving previous job			*b) Classified according to time spent unemployed before joining the program*		
	Men	Women		Men	Women
Marriage or care of children or other relative	0.64	16.89	Less than one month	14.69	11.8
			Between one and two months	26.1	12.87
Market reasons (closure of working place, being fired and end of the job for which he/she was contracted)	43.23	31.1	More than two and up to three months	16.3	15.82
Dissatisfaction with the job or change of address	36.92	38.87	More than three and up to six months	26.93	27.35
To study	19.2	13.14	More than six months	15.98	32.17
Total	100	100	Total	100	100

Table 3
Kaplan Meier empirical survivor functions for trainees
(Proportion remaining in each job status)

	Male with previous working experience			*Female with previous working experience*		
Interval in days	*Initial unemployment*	*Employment*	*Second unemployment*	*Initial unemployment*	*Employment*	*Second unemployment*
0-30	0.66	0.95	0.56	0.79	0.94	0.65

Table 3
(*continued*)

	Male with previous working experience			*Female with previous working experience*		
Interval in days	*Initial unemploy ment*	*Employ ment*	*Second unemploy ment*	*Initial unemploy ment*	*Employ ment*	*Second unemploy ment*
30-60	0.48	0.90	0.42	0.71	0.88	0.50
60-90	0.39	0.85	0.32	0.66	0.82	0.41
90-120	0.33	0.76	0.26	0.60	0.73	0.31
120-150	0.29	0.71	0.23	0.56	0.67	0.25
150-180	0.25	0.68	0.17	0.53	0.64	0.19
180-210	0.21	0.65	0.14	0.49	0.62	0.19
210-240	0.19	0.62	0.10	0.47	0.57	0.11
240-270	0.17	0.59	0.08	0.43	0.56	0.08
270-300	0.16	0.57	0.06	0.40	0.52	0.06
300-330	0.14	0.54	0.04	0.37	0.49	0.02
330-360	0.12	0.51	0.03	0.33	0.46	0.01
360-365	0.11	0.51	0.03	0.32	0.46	0.01
Observations	1432	1369	666	354	268	118
Censored spells	161	773	21	114	153	1
Completed spells	1271	596	645	240	115	117

2.3.2. *Comparison group description and survivor rates of their members*

A sample of unemployed individuals with previous working experience that were looking for a job on the dates on which PROBECAT beneficiaries started their training, but did not participate in it, provided a comparison group of persons that were eligible for the program. The survey was applied to 548 persons (316 men and 232 women). They were part of the National Survey of Urban Employment (ENEU) corresponding to the first quarter of 1993. Additional questions were appended to this survey to capture unemployment and employment spells as obtained in the survey for program participants.[5]

Table 4 indicates the percentage of these individuals that stay in each job status. It can be interpreted in the same terms we did with table 3, corresponding to participants of the training program.

2.4. Statistical model

Hazard models take as the point of departure the definition of a nonnegative continuous random variable T, which represents the spell duration with a density function, $f(t)$. This function $f(t)$ has a corresponding survivor function, simply defined as $1 - F(t)$, i.e., as the probability that duration will equal or exceed the value t (where $F(t)$ is the distribution function). In turn, the hazard function, $h(t)$, is given by:

$$h(t) = \left[\frac{f(t)}{1 - F(t)}\right] \tag{2.1}$$

In this relationship, $h(t)$ can be interpreted as an exit rate or escape rate from the state, because it is the limit (as Δ tends to zero) of the probability that a spell terminates in interval $(t, t + \Delta)$, given that the spell has lasted t periods. Some people who started a spell of employment/unemployment in a given job status may still have been in the same status when they were last interviewed. Data for these people are called censored, and they would constitute a problem for a standard regression model where the dependent variable was the length of the spell. If we exclude people with unfinished spells, we throw away part of the data set and introduce a serious bias against people with longer and more recent spells in each of the job statuses. Duration models have the distinct advantage of being able to handle censored data effectively (Kiefer, 1988).

[5] Unlike program participants that were interviewed with base-line and retrospective surveys, those in the comparison group were interviewed using the panel-linked structure of the ENEU survey. The first survey was applied during the first quarter of 1993 and the other ones as individuals were re-interviewed as part of the panel structure of the survey in subsequent quarters.

Table 4
Kaplan Meier empirical survival functions for non-participants

	Male with working experience			*Female working experience*		
Interval in days	*Initial unemployment*	*Employment*	*Second unemployment*	*Initial unemployment*	*Employment*	*Second unemployment*
0-30	0.80	0.96	0.90	0.87	0.98	0.86
30-60	0.63	0.95	0.77	0.73	0.97	0.76
60-90	0.42	0.89	0.74	0.64	0.93	0.72
90-120	0.35	0.82	0.66	0.61	0.86	0.68
120-150	0.31	0.76	0.51	0.54	0.75	0.63
150-180	0.27	0.67	0.37	0.48	0.71	0.51
180-210	0.23	0.64	0.37	0.45	0.63	0.51
210-240	0.21	0.60	0.37	0.41	0.57	0.51
240-270	0.18	0.55	0.31	0.40	0.56	0.51
270-300	0.17	0.51	0.31	0.37	0.54	–
300-330	0.14	0.49	–	0.35	0.44	–
330-360	0.13	0.42	–	0.34	0.44	–
360-365	0.13	0.41	–	0.34	–	–
Observations	273	224	71	164	99	35
Completed spells	238	96	35	108	41	13
Censored spells	35	128	36	56	58	22

◇ Mixed proportional hazard (MPH) specification

To estimate hazard rates out of a state we assume a mixed proportional hazard (MPH) specification. This has two parts: a 'baseline' hazard and a 'systematic part'. The former, $h_0(t)$, captures the common hazard among individuals in the population and the latter the individual heterogeneity through the effect of a set of co-variates on the hazard rate. In addition, the systematic part is also composed of two parts: observed individual characteristics, X; and a dummy variable, Z, indicating whether or not the individual participates in the program.[6] A further assumption adopted here is that the 'systematic part' of the hazard takes form of an exponential function. Thus, the hazard rate is multiplicative in all the separate elements of the co-variates, *viz*:[7]

$$h(t|X, Z) = h_0(t)\exp(X\beta + Z\gamma) \tag{2.2}$$

The survival and baseline function can be calculated by:

$$S(t; X) = S_0(t)\int_0^t \exp(X\beta + Z\gamma)du \tag{2.3}$$

$$S_0(t) = \exp - \int_0^t h_u du \tag{2.4}$$

Where $S(t; x)$ is the survivor function represented by $(1 - F(t))$ in the denominator of (1).

The conditional density function of the realized t (duration of leaving the state), conditional on X and $Z, t|X, Z$, follows from multiplying (2.2) and (2.3). Hence expected duration in the state is given by:

$$ED = \int_0^\infty tf(t|X, Z)du = \int_0^\infty th(t|X, Z)S(t; X)du \tag{2.5}$$

◇ Multispell proportional hazard models

By construction, the duration of the first post-training job, t_e, starts after the moment at which the first spell of unemployment t_{u1} is realized. Multispell MPH models enable us to capture the dependence between states by including t_{u1} as an additional covariate in the hazard for t_e.[8]

6 This assumes that the different services provided by the multidimensional nature of the training program are adequately captured by a single binary variable.

7 $h_0(t)$ gives the shape of the hazard function for any given individual and the level of the hazard function is allowed to differ across individuals.

8 *Cfr.* Van den Berg (1999) for a survey.

In turn, the dependence between the length of the second spell of unemployment after training (t_{u_2}) and the duration of the previous two states, t_e and t_{u1}, can also be captured. This is achieved by including these two duration variables as additional co-variates of the systematic part in the estimation of the hazard rate of exiting the second period of unemployment. Hence, in the subsequent section we present the results of the following three models:

$$h_{u1}\left(t_{u1}|X,Z\right) = h_{0u1}\left(t\right)\exp\left(X\beta + Z\gamma_0\right) \tag{2.6}$$

$$h_e\left(t_e|X,Z,t_{u1}\right) = h_{0e}\left(t\right)\exp\left(X\beta + \alpha_0 t_u + Z\gamma_1\right) \tag{2.7}$$

$$h_{u2}\left(t_{u2}|X,Z,t_e,t_{u1}\right) = h_{0u2}\left(t\right)\exp\left(X\beta + \alpha_1 t_e + \alpha_2 t_{u1} + Z\gamma_2\right) \tag{2.8}$$

where $h_{u1}(t_{u1}|X,Z)$, $h_e(t_e|X,Z,t_{u1})$ and $h_{u2}(t_{u2}|X,Z,t_e,t_{u1})$ state, respectively, for the hazard rates out of: *a*) first unemployment to employment, *b*) first post-training job to unemployment and *c*) second unemployment to employment.

◇ Co-variates specification

In the estimations conducted in this work, and discussed in the next sections, the co-variates of the systematic part, X, include individual characteristics such as head of household, level of formal education, age, sex and marital status, as well as time spent without a job before the date in which training program started; characteristics of his/her previous job according to whether it was in formal or informal sector, whether it was part or full time and if the person was self-employed or wage earner; and type of occupation; and reasons why the previous job was left.[9]

In turn, the parameters α_0, α_1 and α_2 capture dependence between the time the individual requires to exit one state and that required to exit the previous one(s). The parameters that capture the effect of the training program on the re-employment dynamics of beneficiaries are γ_0, γ_1 and γ_2.

For the subsample of individuals registered in the school-based modality of the program, we measure how does the program's impact differ among sets of institutions providing the training. Given that they have branches

[9] These are presented and detailed in the appendix.

across the country, we further calculate their impact by geographic zones. Hence, the binary variable Z (where zero indicates no participation in training program and unity indicates participation) is included together with two dummy variables that interact with it. One associated with the type of institution in which the training was offered and the other with the geographic zone in which the institution was located.

For the subsample of persons trained in the mixed modality we only calculate how does the impact of the program differs by geographic location. Hence, these estimations include a binary variable corresponding to participation in the program with dummies that capture differences in location interacting with it.[10]

2.5. Results

We divided the group of participants into two sets depending on program modality (school-based or mixed). For each modality we estimated separate models for men and women of hazard models out of unemployment and employment specified by (2.4) and (2.5). It is only for men in the school-based modality that specification (2.6) is also estimated. For the rest, there were not enough observations to estimate hazard rates out of the second unemployment spell, h_{u2}.

In order to avoid bias attributed to unbalanced samples of participants and non-participants in our estimations, we adjusted away differences between group members' characteristics. We paired each participant with an individual in the comparison group who had similar pre-program observable characteristics. For this procedure we applied matching techniqes, whose details are relegated to an appendix. When there was more than one control candidate for a trainee, the matched person was randomly selected among non-participants candidates, fulfilling a matching *criterium*.

The hazard function results for the school-based modality case are presented in tables 5 and 6 and discussed in the following subsection. Those for the the mixed modality are presented in table 7 and their interpretation is presented at the end of the section.

From the specification of these models follows that the larger the parameter $\exp(\beta)$, the higher the hazard rate out of the state. (That is, the

[10] As mentioned above, the mixed modality consists of in-service training in firms. Therefore, no institution is associated with this modality.

more probable it is that the individual will exit the job status, given that the spell has lasted t periods).[11]

Table 5

Male participants in the school-based training modality
Estimated parameters of proportional hazard functions

Variables	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$	h_{u2} $\exp(\beta_i)$
Left job due to marriage or care of relative	1.125 (0.357)	3.32 (2.953)	1.4755 (0.913)
Left job due market reasons	1.152 (1.771)	1.29 (2.224)	0.9974 (-0.017)
Left job voluntarily due to dissa tisfaction or change of address	1.426 (4.506)	0.99 (-0.017)	1.1774 (1.116)
zone2	0.853 (-1.774)	0.77 (-2.098)	5.9327 (7.377)
zone3	0.806 (-2.011)	0.78 (-1.571)	4.2038 (4.914)
zone4	0.72 (-1.729)	1.49 (1.801)	0.5549 (-0.573)
zone5	0.427 (-5.746)	3.02 (5.482)	0.0418 (-15.609)
zone6	0.981 (-0.203)	0.74 (-1.899)	9.6288 (8.936)
Head of household	1.313 (3.650)	0.72 (-3.040)	1.1609 (0.997)
Single	0.791 (-3.085)	0.79 (-2.159)	0.5945 (0.997)
Unempl. between 1 and 2 months	0.979 (-0.298)	0.77 (-2.518)	1.1021 (0.670)
Unempl. between 2 and 3 months	0.926 (-0.929)	0.63 (-3.818)	1.4825 (2.362)

[11] To facilitate the interpretation that follows, explanatory variables related to the effects of the program, to the age of the participant, or to the time dependence between states appear in the second half of these tables with their corresponding β coefficient.

Table 5
(*continued*)

Variables	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$	h_{u2} $\exp(\beta_i)$
Unempl. between 3 and 6 months	0.913 (-1.281)	1.06 (0.644)	1.2925 (1.731)
Unempl. more than 6 months	0.603 (-5.708)	1.3 (2.243)	0.8662 (-0.786)
Full time wage-earner, formal sector	1.159 (1.305)	1.31 (1.486)	1.0319 (0.134)
Part time wage-earner	0.677 (-2.607)	1.25 (0.995)	1.0463 (0.155)
Full time self employed	1.02 (0.163)	1.32 (1.511)	0.9331 (-0.276)
Full time wage-earner, informal sector	1.301 (2.229)	0.92 (-0.431)	1.0761 (0.303)
	Coef(β)	Coef(β)	Coef(β)
Age	0.048 (2.733)	-0.009 (-0.325)	-0.034 (-0.955)
Age Squared	-0.001 (-3.966)	0.000 (0.018)	0.000 (0.318)
t_{u1}		0.003 (6.849)	0.004 (5.745)
t_e			0.003 (5.012)
Dummy for being in PROBECAT, Z	0.045 (0.398)	-0.785 (-4.704)	2.20769 (8.5123)
Z:zone2	-0.079 (-0.583)	0.426 (2.287)	-1.940 (-6.766)
Z:zone3	0.057 (0.397)	0.457 (2.249)	-1.489 (-4.510)
Z:zone4	0.226 (0.945)	-0.138 (-0.461)	0.931 (0.885)
Z:zone5	0.894 (4.874)	-1.340 (-5.149)	NA

Table 5
(continued)

Variables	h_{u1}	h_e	h_{u2}
	Coef(β)	Coef(β)	Coef(β)
Z:zone6	-0.156 (-1.148)	0.269 (1.291)	-2.661 (-8.807)
Z:CONALEP	-0.159 (-2.013)	0.135 (1.146)	0.131 (0.918)
Z:CECATI	-0.092 (-1.031)	0.240 (1.829)	-0.478 (-3.006)
Z:CEBETI	0.217 (2.067)	0.306 (2.058)	-0.181 (-1.004)
Z:PRIVATE	0.118 (0.460)	0.154 (0.411)	-0.566 (-1.166)
Z:CETI	-0.670 (-3.255)	-0.246 (-0.651)	-0.580 (-0.962)
Log Likelihood ratio test	596	553	506

Notes: Each of these functions also control for five categories of education level and for nine categories of previous job ocupation. Corresponding parameters not included in the table, they are relegated to the appendix.

The statistic presented is the value of the coefficient divided by its standard error. When it is within $\pm$ 1.96, implies that the co-variant is significant at the 5% confidence level. If one of the co-variates belonging to a nested subset is significant, then the related ones are as well, even if their statistic values are above the critical value.

2.5.1. *School-based training modality*

◇ Individual characteristics and location as determinants of hazards out of unemployment and employment

The results in the first three rows of the first and second column of table 5 show that men who left their previous job because they were dissatisfied with it –or because they moved to another address– found a job faster than the rest and stay longer in a it. That is, they hold on to their jobs for a relatively longer period, when compared to those that left their job due to market reasons, to marry, to take care of relatives, or to study (which does not appear in the table, because it is the reference variable).

Table 6

Female participants in the school-based training modality
Estimated parameters of proportional hazard functions

Variables	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$
Left job due to marriage or care of relative	0.361 (-3.806)	0.2121 (-2.995)
Left job due market reasons	1.088 (0.412)	0.1491 (-4.195)
Left job voluntarily due to dissatisfaction or change of address	0.963 (-0.200)	0.2058 (-3.778)
zone2	0.406 (-3.020)	0.6866 (-0.825)
zone3	0.382 (-3.299)	0.2512 (-3.205)
zone5	0.192 (-4.476)	0.5038 (-0.941)
zone6	0.394 (-3.411)	0.8212 (-0.418)
Head of household	2.116 (3.626)	4.9063 (3.979)
Daughter	1.725 (2.192)	2.2452 (1.778)
Single	1.115 (.520)	0.7515 (-0.801)
Unempl. between 1 and 2 months	1.479 (.871)	0.516 (-1.662)
Unempl. between 2 and 3 months	0.911 (0.417)	1.4015 (0.939)
Unempl. between 3 and 6 months	0.849 (0.820)	0.9215 (-0.208)

Table 6
(continued)

Variables	h_{u1} $\exp(\beta_i)$	h_ϵ $\exp(\beta_i)$
Unempl. more than six months	0.605 (-2.325)	1.1492 (0.362)
Full time wage-earner, formal sector	1.818 (2.461)	1.3053 (0.667)
Part time wage-earners	0.833 (-0.669)	1.5714 (0.934)
Full time self employed	1.358 (0.913)	0.4677 (-1.290)
Full time wage-earner, informal sector	1.325 (1.148)	1.3018 (0.643)
	Coef(β)	Coef(β)
t_{u1}		0.0013 (0.985)
Age	0.112 (2.215)	0.215 (2.480)
Age Squared	-0.0014 (-1.887)	-0.0037 (-2.738)
Dummy for being in PROBECAT, Z	-1.065 (-3.1477)	-0.714 (-1.323)
Z:zone2	0.798 (2.13)	0.71 (1.184)
Z:zone3	0.916 (2.461)	1.839 (1.184)
Z:zone5	1.393 (3.145)	-0.302 (-0.36)
Z:zone6	0.352 (0.948)	-0.37 (-0.532)
Z:CONALEP	0.062 (0.236)	0.273 (0.611)
Z:CECATI	0.067 (0.247)	-0.823 (-1.841)

Table 6
(continued)

Variables	h_{u1} Coef(β)	h_e Coef(β)
Z:CEBETI	-0.308 (-0.96)	-1.459 (-2.756)
Z:PRIVATE	0.089 (0.199)	-0.94 (-1.393)
Z:CETI	0.042 (0.105)	-0.229 (-0.337)
Likelihood ratio	295	145

Notes: Each of these functions also control for five categories of education level and for nine categories of previous job ocupation. Corresponding parameters not included in the table, they are relegated to the appendix.

The statistic presented is the value of the coefficient divided by its standard error. When it is within ± 1.96, implies that the co-variant is significant at the 5% confidence level. If one of the co-variates belonging to a nested subset is significant, then the related ones are as well, even if their statistic values are above the critical value.

In contrast, as follows from corresponding figures in table 6, women who left their previous job to get married or to take care of a relative took longer to exit unemployment. However, once employed, they stay in their jobs for a length of time that does not differ from that of the rest.

The relatively frequency of movements in and out of jobs that characterizes the labor force in each region of the country has been captured by the covariates corresponding to geographic zones. For example, estimates presented in table 5 indicate that it takes more than twice as long for a man to find a job in the southwestern region of Mexico (Zone 5), that it does to one in the western zone (Zone 1, which is the reference).[12] In turn,

[12] Note that one minus the inverse of the coefficient $\exp(\beta)$ provides an indicator of the percentage reduction in time required to find a job, relative to the reference group. For example, when $\exp(\beta)$ is 1.15 the expected time is approximately $1/1.15=0.869$, that is there is a reduction of approximately 14% in time with respect to the reference. On the other hand, when $\exp(\beta)$ is .047, the approximated expected time is $1/0.47=2.12$, which implies an increase of 112% *-viz* the double- in time with respect to the reference.

once they find it, the worker in the western zone lasts three times longer in that job, relative to a worker in the West. Moreover male workers in zone 5 have lower transition rates out of their initial unemployment state, lower job retention rates and, as follows from rows four to eight in the column corresponding to h_{u2}, also spend longer looking for another job, if they loose their first job.

Results in table 5 indicate that the hazard rate out of unemployment of a man that has been unemployed for six months or more is lower than that of a man who has spent less than one month looking for a job (which is the reference variable): it takes the former more than twice as long as the latter to find a job. In addition, when those men unemployed for more than six months find a job, they held on to it for less time.

Table 7

Participants in the mixed training modality
Estimated parameters of proportional hazard functions

Variables	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$
	Male		*Female*	
Left job due to marriage or care of relative	NA		0.803 (-0.3937)	0.2483 (-1.1735)
Left job due market reasons	0.549 (-1.401)	1.641 (0.7599)	7.054 (3.6027)	0.0304 (-3.0746)
Left job voluntarily due to dissatisfaction or change of address	0.737 (-0.729)	0.553 (-0.9209)	5.501 (3.4332)	0.1218 (-1.9415)
zone2	0.783 (-0.655)	0.483 (-1.8646)	2.032 (1.2715)	1.8225 (0.7956)
zone3	0.562 (-1.246)	1.185 (0.2924)	0.712 (-0.8923)	0.9352 (-0.1051)
zone5	0.319 (-1.421)	2.597 (1.407)	0.515 (-1.4518)	0.6111 (-0.6359)
Head of household	1.659 (1.551)	1.557 (1.0005)	0.808 (-0.6925)	1.2275 (0.3544)
Daughter			0.548 (-1.0464)	1.0232 (0.0296)

Table 7
(continued)

Variables	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$
	Male		*Female*	
Unempl. between 1 and 2 months	0.96 (-0.146)	0.42 (-1.8271)	1.236 (0.609)	1.5483 (0.6679)
Unempl. between 2 and 3 months	1.18 (0.464)	2.063 (1.4351)	0.786 (-0.6389)	9.0593 (3.2609)
Unempl. between 3 and 6 months	1.268 (0.823)	1.991 (1.5095)	0.952 (-0.1464)	1.0296 (0.0401)
Unempl. more than 6 months	0.395 (-2.229)	0.984 (-0.0269)	0.664 (-1.0193)	1.0975 (0.1274)
Single	1.172 (0.494)	0.675 (-0.9847)	3.098 (2.0246)	0.2369 (-2.4432)
Full time wage-earner, formal sector	1.553 (0.637)	2.352 (1.2157)	2.069 (0.9446)	0.191 (-1.4324)
Part time wage-earners	0.338 (-1.09)	4.296 (1.5449)	0.775 (-0.3187)	0.0769 (-1.9692)
Full time self employed	1.341 (0.398)	3.203 (1.5172)	2.177 (0.9312)	0.1702 (-1.2993)
Full time wage-earner, informal sector	2.538 (1.288)	1.578 (0.6425)	2.147 (1.0107)	0.2772 (-1.2321)
	Coef(β)	Coef(β)	Coef(β)	Coef(β)
Age	0.112 (1.366)	-0.352 (-2.8741)	0.0343 (0.3758)	-0.176 (-1.1205)
Age Squared	-0.001 (-1.306)	0.004 (2.5526)	-0.0001 (-0.0989)	0.003 (1.4948)
t_{u1}		0.002 (1.3551)		0.004 (3.2691)
Dummy for being in PROBECAT,Z	0.418 (1.496)	-1.146 (-3.11)	-1.288196 (-1.6355)	1.862 (1.4909)
Z:zone2	-0.153 (-0.317)	0.558 (0.9905)	0.746 (0.7808)	-3.254 (-2.2158)

Table 7
(*continued*)

Variables	h_{u1} Coef(β)	h_e Coef(β)	h_{u1} Coef(β)	h_e Coef(β)
Z:zone3	0.134 (0.144)	0.213 (0.1995)	1.325 (1.5967)	-3.367 (-2.3041)
Z:zone5	2.170 (1.851)	-1.020 (-0.7562)	-0.572 (-0.5313)	NA
Log likelihood ratio test	103	103	188	130

Notes: Each of these functions also control for five categories of education level and for nine categories of previous job ocupation. Corresponding parameters not included in the table, they are relegated to the appendix.

The statistic presented is the value of the coefficient divided by its standard error. When it is within ± 1.96, implies that the co-variant is significant at the 5% confidence level. If one of the co-variates belonging to a nested subset is significant, then the related ones are as well, even if their statistic values are above the critical value.

Heads of household, whichever the gender, spend less time finding a job. Married men stay in their jobs longer. In turn, men and women with previous work experience as part time wage-earners require more time to find a job compared to full-time wage earners and self-employed individuals, but only the women in this group have higher hazard rates out of employment. The parameters corresponding to level of education and type of occupation in previous job were also calculated, but were relegated to the appendix. They turned out to be statistically significant, but presented no distinguishable pattern. For women and men hazard rates out of unemployment increase with age up to a threshold at which the event of finding a job becomes less likely. For women, this threshold is 40 years.[13]

◇ The impact of training on re-employment dynamics

A quantitative calculation of the program's impact, by modality en each reagion –and also by type of institution providing training services in the

[13] For men the results imply a threshold of 24 years.

former case– requires combining coefficients estimated in the hazard function. (Three in the school based modality and two in the mixed modality). Thus, the value of these parameters, and not their exponential values, appear in the last rows of tables 5 and 7. The quantitative calculation of the effect of school-based training appears in tables 8 and 9.

Table 8

Impact of the school-based modality training on men
Computed parameters of proportional hazard functions

Type of institution	*Zone1*	*Zone2*	*Zone3*	*Zone4*	*Zone5*	*Zone6*
A: *Transition rates out of initial unemployment*						
PRIVATE	1.2	1.09	1.31	1.5	2.87	1.02
CONALEP	0.9	0.81	0.98	1.12	2.15	0.76
CECATI	0.95	0.86	1.03	1.18	2.27	0.8
CEBETI	1.28	1.16	1.39	1.6	3.06	1.09
CETI	0.54	0.49	0.59	0.68	1.29	0.46
Other	1.05	0.95	1.14	1.31	2.51	0.89
B: *Transition rates out of employment*						
PRIVATE	0.54	0.82	0.9	0.47	0.14	0.7
CONALEP	0.52	0.79	0.88	0.46	0.14	0.68
CECATI	0.58	0.88	0.97	0.51	0.15	0.75
CEBETI	0.62	0.94	1.04	0.54	0.16	0.81
CETI	0.37	0.56	0.62	0.33	0.1	0.48
Other	0.46	0.69	0.77	0.4	0.12	0.6
C: *Transition rates out of second unemployment*						
PRIVATE	6.88	0.86	1.71	16.67	16.85	0.5
CONALEP	13.17	1.65	3.28	31.93	32.28	0.95
CECATI	7.43	0.93	1.85	18	18.2	0.53
CEBETI	10.01	1.25	2.49	24.27	24.53	0.72
CETI	15.53	1.95	3.87	37.64	38.05	1.12
Other	12.26	1.54	3.05	29.71	30.04	0.88

The cells in tables 8 and 9 present the exponential value of the sum of the β coefficients corresponding to the dummy variable for being in the treatment group and to the interactive dummies for zone and type of institution (*viz*, the coefficients of corresponding covariates in the hazard functions in tables 5 and 6). They represent the impact of training by set of institutions on re-employment dynamics, according to the geographic zone in which they are located.

In these tables, values larger than one in hazard rates out unemployment, indicate that training offered by that institution is effective. The larger the value, the more effective the program is in speeding up the job search process.[14] In turn, in the tables representing hazard rates out employment, values below one imply that the institution providing the training is effective in improving the employment dynamics of their trainees. The inverse of the coefficient indicates the percentage increase in the amount of time that they hold on to their jobs, as a result of participation in the program.

◇ Hazard rates out of unemployment: the impact by location and type of institution

Previous evaluations of the impact of this program in reducing the time required to leave unemployment concluded that the school-based modality was ineffective for men and effective for women (*e.g.* Aportela (2003). However, these studies considered only the impact of the program at a national level, aggregating all institutions providing this service. Thus, their conclusions are applicable only on average, and they could be misleading in concluding, without further analysis, that the program was overall useless for men and effective for women. We show here that the impact of the program differed in magnitude and in cases also in sign, according to the geographic area and the type of institution providing training.

Figures in table **8A** show that men trained in CONALEP, CECATI and CETI were not able to find a job more quickly in zones 1, 2 and 6.[15] This result coincides with what was pointed out in previous evaluations. However, this table also shows that contrary to what previous evaluations would suggest, men trained in the other zones of the country experienced a positive impact. Results in fourth and fifth columns indicate that, in general, in the southern states of Mexico (Zone 5) and in the in-bond northern region

[14] For effective institutions, calculating one minus the inverse of the coefficient which appears in each of the cells of the table indicates the percentage reduction in the number of days required to find a job (relative to the counterfactual of having not received the training provided by program).

[15] Except for the case of CECATI, this is also the case in Zone 3, whereas in Zone 4 CETI was also ineffective.

(Zone 4)[16] men took less time to find a job if they joined the program, no matter what institution trained them.[17] Also, results for men with working experience trained by institutions run by the private sector and by CEBETI show the importance of capturing effects by type of institutions. These training institutions were effective in all the zones examined, as shown in the first and fourth rows of table 8**A**.

Table 9

Impact of the school-based modality training on women
Computed parameters of proportional hazard functions

Type of institution	*Zone1*	*Zone2*	*Zone3*	*Zone5*	*Zone6*
A: *Transition rates out of initial unemployment*					
PRIVATE	0.38	0.84	0.94	1.52	0.54
CONALEP	0.37	0.81	0.92	1.48	0.52
CECATI	0.37	0.82	0.92	1.48	0.52
CEBETI	0.25	0.56	0.63	1.02	0.36
CETI	0.36	0.8	0.9	1.45	0.51
Other	0.34	0.77	0.86	1.39	0.49
B: *Transition rates out of employment*					
PRIVATE	0.19	0.39	1.2	0.14	0.13
CONALEP	0.64	1.31	4.04	0.48	0.44
CECATI	0.21	0.44	1.35	0.16	0.15
CEBETI	0.11	0.23	0.72	0.08	0.08
CETI	0.39	0.79	2.45	0.29	0.27
Other	0.49	1	3.08	0.36	0.34

As it was the case for men, table 9**A** indicates that all institutions providing PROBECAT services in Zone 5 helped women with prior working experience find a job faster. *Per contra*, in the rest of the country none

[16] With the exception of CETI.

[17] It is in Zone 5 where CEBETI had the biggest impact: men in this zone required 67% less time to find a job relative to what would have been the case if they had not received the services provided by the program.

of the institutions were able to improve employment prospects for women with previous working experience.

◇ Hazard rates out of employment and out of a second unemployment spell: the impact by location and type of institution

In the western region of the country (Zone 1), men trained in CONALEP or in CECATI did not find a job faster. Based only on this result, which appears in the second and third rows of table 8**A**, it would seem that the training programs provided in the western region of Mexico are not effective in improving employability prospects of men. However, figures in the cells of the second and third rows of the first column of tables 8**B** and 8**C** indicate that: in net terms, the impact of the program on men's re-employment dynamics is positive and important. Men trained by these institutions in zone 1 held on to their jobs for a longer period of time, and those that left their job found another one relatively faster. These two effects implied that participants work more days during a year thanks to the program and that they compensated for the fact the participants took longer to exit the initial post-training unemployment state.

This case illustrates that the impact of a training program on reemployment dynamics of its beneficiaries must explicitly consider two questions, in addition to how quickly individuals find a job after their training. First, were they able to increase the time employed in their first post-training job? Second, did they need less time to find another job, if the first post-training job was lost?

Training provided to men by CEBETI in Zone 3 illustrates a case in which it is usefull to distinguish and effective program which helps participants find jobs from another one that helps them to hold on to their jobs. Although the training provided by this institution was unable to extend the time that its trainees spent employed, it was effective in reducing both unemployment spells.

The program was overall effective in improving men's employability prospects in only a few cases. By overall effective, we mean that men not only found jobs faster than they would have had if they not joined the training program, but also that they remained employed for longer and found another one relatively faster if that job was not retained. These overall effective cases were those institutions located in the in-bond (maquiladora) region, in the northern border and in the south of Mexico (i.e. in zones 4 and 5[18]); the CEBETI institutions in the West and North of the country

[18] With the exception of transition rates out of initial unemployment if trained in CETI in zone 4.

(zones 1 and 2); and private institutions in zones 1 and 3. In the other cases, the impact of the program on employment retention was positive but most of them did not achieve the aim of helping beneficiaries find a job faster.

As was the case with men, we found that the impact of the program on the women differed widely, depending the institution offering the training, and the region in which the training was offered. We found that the most effective institutions, and the zones in which they were most efficient, were not the same for the women as for the men. Those trained in CONALEP in Zone 2 did not benefit from the school-based modality of PROBECAT. This is also the case for women in the states along the east coast of Mexico (Zone 3), with the exception of those who participated in the CEBETI program, whose net effect is ambiguous because of a positive effect on employment retention counteracting an adverse effect on helping to find a job faster.

It is only in the southern states of Mexico (Zone 5), where we can have an unambiguous conclusion, namely that all institutions offering the services of PROBECAT to women are effective in helping their trainees reduce the time required to find a job as well as in increasing the time they hold on to their job. The women trained in the rest of the country benefited from the program by holding on to their jobs for longer, but not by finding a job faster.

◇ Heterogeneous impact of training on individuals with different characteristics

We consider now the relative impact with which training benefit two types of participants: a) male trainees with more than six months in unemployment before joining the program and b) women who left their previous job because they married or to take care of children or relatives. This requires of alternative variants of our estimated hazard functions for the school-based modality. They differ with respect to the ones presented in tables 5 and 6 only in their inclusion of another dummy variable with a pre-treatment observable characteristic of interest interacting with the dummy variable indicating program participation.[19]

In the previous subsection we concluded that institutions located in zones 4 and 5 were effective in increasing the hazard rates out of unemployment of men participating in the program. We can further assess this result. Table 10**A** presents the impact of training on men. These figures indicate that, although all the participants of zones 4 and 5 benefited from

[19] The corresponding tables are not included in the text, but they are available upon request from the author.

the program, men who had been unemployed for more than six months before joining the program benefited most with the services provided by the program.

This result is further substantiated when we consider what happened with men trained in zones 1, 2, 3 and 6. Table 10**A** reveals the following: while men who were unemployed for less than six months took longer to find a job, those who were unemployed for more six months before joining the program found a job relatively faster than what would have been the case if they have not participated in it. In addition, those that had been unemployed for more than six months before joining the program benefited most in terms of staying in their new jobs for longer. This result is shown in table 10**B**. Figures in this table also show that, in four out of six zones, male participants that had been unemployed for one to two months did not benefit in terms of holding on to their jobs for longer.

Table 10

Impact of the school-based modality training on women
Computed parameters of proportional hazard functions

Length of unemployment before beginning their training	*Zone1*	*Zone2*	*Zone3*	*Zone4*	*Zone5*	*Zone6*
A: *Transition rates out of unemployment*						
Unempl. for less than 1 month	0.99	0.96	1.06	1.31	2.43	0.85
Unempl. for less than 1 month	0.99	0.96	1.06	1.31	2.43	0.85
Unempl. between 1 and 2 months	0.95	0.92	1.02	1.26	2.33	0.82
Unempl. between 2 and 3 months	0.87	0.84	0.93	1.15	2.14	0.75
Unempl. between 3 and 6 months	0.8	0.77	0.86	1.06	1.96	0.69
Unempl. more than 6 months	1.39	1.35	1.49	1.84	3.42	1.2
B: *Transition rates out of employment*						
Unempl. for less than 1 month	0.42	0.73	0.95	0.46	0.12	0.54

Table 10
(*continued*)

Length of unemployment before beginning their training	*Zone1*	*Zone2*	*Zone3*	*Zone4*	*Zone5*	*Zone6*
Unempl. between 1 and 2 months	0.94	1.66	2.17	1.03	0.28	1.22
Unempl. between 2 and 3 months	0.77	1.35	1.76	0.84	0.23	0.99
Unempl. between 3 and 6 months	0.32	0.57	0.74	0.36	0.1	0.42
Unempl. more than 6 months	0.21	0.37	0.49	0.23	0.06	0.27

Tables 11**A** and 11**B** present, in turn, the program's impact on re-employment dynamics of women when dummy variables representing reason for leaving last job interact with the dummy variable indicating program participation. There is no impact on women who left their job because of market reasons. Figures in the second row of these tables indicate that they were not able either to find a job faster or to hold on to a job for longer period. *Per contra*, the women that benefited in both cases from the program were those that left their job because of marriage or to take care of their children and other relatives.

◇ Indirect effects of trainning on employment and subsequent unemployment spells

The duration of the initial unemployment spell after training appears in our specification (2.5) as a co-variate in the hazard function out of employment and in (2.6), together with the first employment spell as a covariates in the hazard function out of the second unemployment spell. As explained in the previous subsection, in view of the multi-spell nature of the estimation of the hazards, the inclusion of these co-variates captures indirect effects of trainning on employment and subsequent unemployment spells. Its relevance for exits out of a second unemployment spell are given in the third column of table 5. The positive and significant value for the covariate time spent in the post-training job, t_e, indicates that individuals that benefit from training programs by holding on to their job for longer also benefit in that they find another job faster when they leave their first post-training job. The value of this coefficient, .003, implies that an additional month employed reduces by 10% the time spent looking for new employment, when that job is lost. In turn, the positive effect of the unemployment spell variable t_{u1} could be interpreted as following: if the individual researches prospective jobs more intensively in the first episode, then less time is required to find another job in the event of a second unemployment spell, since the individual is more familiar with the job market.

Table 11
The impact of the school-based modality on women
Computed parameters of proportional hazard functions

Reasons for leaving	*Zone1*	*Zone2*	*Zone3*	*Zone5*	*Zone6*
A: *Transition rates out of initial unemployment*					
Marriage or care of children or other relative	3.31	8.19	7.05	11.02	3.71
Market reasons	0.28	0.69	0.59	0.92	0.31
Dissatisfaction with job or change of address	0.23	0.57	0.49	0.77	0.26
To study	0.76	1.88	1.62	2.53	0.85
B: *Transition rates out of initial employment*					
Marriage or care of children or other relative	0.14	0.17	0.48	0.14	0.22
Market reasons	1.26	1.51	4.40	1.27	1.97
Dissatisfaction with job or change of address	0.20	0.24	0.69	0.20	0.31
To study	0.03	0.04	0.11	0.03	0.05

2.5.2. *Impact effect of the on-the-job training modality*

As shown in table 12**A**, the mixed modality of the program was overall effective in improving the re-employment dynamics of men with working experience. The positive effects were most pronounced in zone 5.

Table 12

Impact of Mixed Modality on re-employment dynamics
Computed parameters of proportional hazard functions

	Men		*Women*	
	Transition rates out		*Transition rates out*	
	of unemployment	*of employment*	*of unemployment*	*of employment*
Zone1	1.59	0.317	0.58	0.25
Zone2	1.3	0.555	1.04	0.22
Zone3	1.78	0.393	0.15	NA
Zone5	13.31	0.114	0.27	6.44

In turn, table 12**B** shows that women that participated in the mixed training modality of PROBECAT in zones 1 and 2 (where 93% of respondents were located) benefited by increasing the time they hold on to their jobs. It is only in Zone 2 where they benefit as well by getting a job relatively faster than would have been the case if they have not joined the program.

2.6. Projecting and assessing the impact of the program

Hazard functions are usefull not only to estimate the program's effectiveness in increasing the employability prospects of their beneficiaries within the sampling frame of an evaluation. They are also usefull to simulate and project the impact of the program on re-employment dynamics of participants in two directions: predicting employment rates beyond the end of the sampling frame and projecting its effectiveness in different environments from the one where it was experienced. We illustrate their use next.

◇ Impact on survivor rates in employment

Once the parameters for the hazard functions have been obtained, survivor functions estimates, as stated in equation (2.3) in section 3, follow from a straitforward application of a formula. The difference between the survival-time in unemployment and employment by participants, conditioning on individual characteristics, and their survival time in the hypothetical case of non- participation can then be computed. This procedure provides required information for a quantitative assesment of the program's benefits atributed to increasing the employability prospects of their beneficiaries, for the time framework in which the evaluation was conducted. Alternatively, with a relationship such as equation (2.4), it is possible to estimate mean duration in each state and calculate the fraction of time spent by program participants in employment within a given period after their training finished, *e.g.* 18 months, as refered to the date in which surveys were applied- and compared it with the counterfactual results based on corresponding calculations for non-participants with same caracteristics.

a) Predicting beyond the sampling framework

It is worth stressing these formulae can also be applied to periods that are beyond the time framework in which the evaluation was conducted. Thereby allowing to predict medium term impacts of the program. In turn, with hazard functions is also possible to address questions such as the following one: Given that a type of institution providing training in the rest of the country has not been offering its services in a region, would it performe well there? That is, hazard functions are usefull to estimate the likely effectiveness of the program in different environments from the one where it was experienced. As an example of this, consider the case of PROBECAT training provided by private institutions. For the cohort of male elegible individuals to which the sample used in this study was applied, training this kind of institution was only available in zones 1 and 2. In spite of this, based on our hazard function estimates, we can assess what could had happen if they were also available in zones 3, 4 and 6. This is shown in table 8.

Our estimates indicate that private institutions in zones 4 and 5 would have performed effectively and would have achieved better results than they did in zones 1 and 2. In addition, in this part of the country they would have outperformed CECATI and CEBETI in helping men find a job faster and in keeping it for a longer period.

b) Implications for cost benefit analysis

By increasing hazard rates out of unemployment and lowering hazard rates out of employment, a program might indirectly achieve the objective of improving human capital of persons exposed to the skill improving activities associated to working. This indirect effect might not be reflected in a short period of time and therefore program evaluation might not find an impact of the program on post-training wages. Therefore, the effect that a program for unemployed workers has on the earnings of its beneficiaries must not be measured exclusively in terms of its short-term impact on wages.[20] It must consider the impact it might have on their yearly earnings due to a reduction in time searching for a job and an increase in the time they hold on to their jobs. That is, in cost-benefit analysis of training programs, the net cost of training per participant is compared with benefits attributed to them. These benefits are assumed to occur within a certain time span (*e.g.* in a year or a number of years). Hence, since improving the job prospects of unemployed workers is one of the objectives of the program, then an integral cost-benefit analysis must quantify its impact on earning due to changes in number of weeks an individual worked during a year, relative to what would have been the case if they have not joined the program.

2.7. Concluding remarks

Along with demands for transparency of public spending, there has been a growing consensus in developing countries that the future of their active labor market programs should be decided based on adequate measurements of their impact on performance of their beneficiaries.[21] The analysis conducted in this paper highlights cases in which benefits attributed to improving re-employment dynamics of participants might, on their own, compensate the cost of a program. We found that in some cases, such as those in the southern states of the county, unemployed individuals trained there not only found jobs faster than what would have been the case had they not joined the program, but they also remained employed for a longer period of time. Moreover, our estimates showed too that male workers that were not able to retain their first post-training job found another one relatively faster than what would have been the case, had they not benefited from the services provided by the program.

We stressed that policymakers need to assess the future of programs for unemployed individuals based on a knowledge of their effectiveness in helping workers achieve good job matches and in helping individuals find a 'sustained' job. This is because they are targeted at individuals characterized by their risks of prolonged periods of inactivity and their propensity to find only casual and temporary employment.

This implies two requirements. The first one, that a program's evaluation must go beyond the impact on wages of beneficiaries or on the probability of finding a job. The second is that an integral cost-benefit analysis that

[20] In cost-benefit analysis of training programs, the net cost of training per participant is compared with benefits attributed to them. These benefits are assumed to occur within a certain time span (*e.g.* in a year or a number of years).

[21] This occurs at times because international agencies, such as IDB, ADB or World Bank, may require it as part of their financial contribution.

can quantify its impact on beneficiaries' earnings due to additional weeks worked in a year, relative to what would have been the case if they have not joined the program. When this is ignored, there is a risk of erroneously considering a program ineffective and questioning its continuation. This is what happened with the program evaluated in this paper. Based on results showing its ineffectiveness to improve wages, a suggestion was put forward to re-classified this program as a safety net providing only temporary relief for the unemployed (Giugale, Lafurcade and Nguyen, 2001). Our results show that it is not only distributional and fairness concerns that justify their fundings. They are consistent with the contention that, even in the absence of a major improvement in daily wage, its benefit through more stable job histories and greater human capital accumulation of participants is large enough to compensate the costs of the program.

These results –as well as the of the other ones in this paper– rely on an important assumption about the determinants of hazard functions. This is that unobserved sources of heterogeneity among individuals (or omitted co-variates) are not important determinants of hazard rates out of unemployment and of employment. If this assumption does not hold, biases in the estimation originate because, on average, individuals with relatively high hazard rates for unobserved reasons (*e.g.* work ethics, self-discipline, availability of precautionary savings or higher intertemporal rates of return) leave unemployment first, and/or stay longer in employment, so that samples of survivors are selected. To check then robustness of the results obtained in this work, we leave for future research the re-estimation of the hazard functions within an estimation framework that relaxes this assumption.[22]

A more elaborate extension to the analysis incorporating unobserved heterogeneity (also called unobserved person specific characteristics) can, in turn, open up the possibility to deal with an important implicit assumption of the evaluation of the effectiveness of this kind of programs. Namely, that there is no selection of program participants.

The work presented here assumes that participants are randomly assigned to the program. For a counterfactual analysis of what would have happened with them, if they had not benefit with the training provided by the program, we worked with non-participant individuals that constituted a comparison group. The random assignation assumption implies that the characteristics that are not observed by the analyst (or ommited from the estimation) of individuals that participate in the program have the same distributions as the one corresponding to non participants. Under this as-

[22] *Cfr.* Meyer (1990), where an estimation strategy to correct for unobserved heterogeneity in single spell hazard models is applied. His strategy, in turn, is an extension of Heckman and Singer (1984) approach.

sumption, it is possible to dissentange the causal effect of training from the selection of program participants with the procedure followed in this work.

When this assumption does not hold, and the unobserved heterogeneity component that affects hazards out of unemployment and/or of employment are correlated with the one that affects participation in the program, a more elaborated estimation is required. The problem that must be addressed then is the following one. If unobserved characteristics of individuals have a negative effect on re-employment dynamics and a positive effect on the propensity to participate in the program, then conditional on the observed characteristics, the average quality of unemployed individuals participating in the program is lower than the average qualitiy of unemployed individuals not participating. Therefore, one would underestimate the true effect of participating in the program. (One would compare hazard rates of workers with unfavorable characteristics participating in the program with hazard rates of workers with more favorable characteristics which not participated). The opposite effect is also possible. When the unobserved heterogeneity component in the propensity to participate in the program is positively correlated with the hazard rate out of unemployment and negative correlated with the hazard rate out of employment, the impact effect of the program is overestimated. This would be the case, for example, when people in control of participation want their programs to be a success. Therefore they prefer workers with good characteristics to participate in the program.

As shown in Abbring and Van den Berg, 2003, multiple-spell data, such as the one used in this paper, are similar to panel data in the sense that the intuition for identification in linear panel-data models carries over to multi-spell hazard models. By exploiting the fact that we observe multiple outcomes for given unobserved heterogeneity values, it is possible to have some separability of the hazards, in progam participation effect and unobserved covariate components. Then, if the unobserved components are constant between spells, variation between spells and within group of individuals can be used to control for selection effects and identify the impact of the program.[23]

This research agenda, consisting of controling for potential selection bias into multiple spells by estimating employment and unemployment jointly with propensity to participate, allowing for full correlation structure of the unobservables, is left for future work.

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[23] Gritz (1993) and Van Ours (2001) apply this procedure. Related studies are Ham and LaLonde (1996), Bonnal, Fougere and Serandon (1997), and Eberwein, Ham and LaLonde (1997) and (2002).

Appendix

Variables used as determinants of the probability of program participation functions and as co-variates in the multispell models.

Reasons why the previous job was left

- Marriage, childbearing care of children or other relative, equals 1, zero otherwise.
- Left their job due to market reasons (fired, end of contract), equals 1, zero otherwise.
- Left their job voluntarily because of a change of address or job dissatisfaction, equals 1, zero otherwise.
- Left their job to study, equals 1, zero otherwise.

Geographic Region[24]

- Zone 1: In Western region of Mexico, equals 1 zero otherwise.
- Zone 2: In Northern region of Mexico, equals 1 for persons zero otherwise.
- Zone 3: In the Coast of Mexico, equals 1 for persons zero otherwise.
- Zone 4: In Bond (maquiladora) Northern Region of Mexico, equals 1 for persons zero otherwise.
- Zone 5. In the South states of Mexico, equals 1 for persons zero otherwise.
- Zone 6: In Mexico City and Central Area of Mexico, equals 1 for persons zero otherwise.

Unemployment duration before the beginning of the training program

- Less than one month equals 1, zero otherwise.
- Between one and two months, equals 1, zero otherwise.

[24] The 'municipalities' that constitute each region are available from the authors upon request.

- More than two and up to three months equals 1, zero otherwise.
- More than three and up to six months equals 1, zero otherwise.
- More than six months equals 1, zero otherwise.

Characteristics of previous job

- Formal sector[25] 1, wage earner and worked more than 35 hours: equals 1, zero otherwise.
- Formal sector, wage earner and worked less than 35 hours: equals 1, zero otherwise.
- Formal sector, non-wage earner (i.e. self-employed) and worked less than 35 hours: equals 1, zero otherwise.
- Informal sector, wage earner and worked less than 35 hours: equals 1, zero otherwise.
- Informal sector, non-wage earner (i.e. self employed) and worked less than 35 hours: equals 1, zero otherwise.
- Formal or informal sector, non-wage earner (i.e. self-employed) and worked less than 35 hours: equals 1, zero otherwise.

Gender: Equals one if female, zero if male.

Age: Units of this variable is in years divided by ten.

Family position

- Head of household: equals one, zero otherwise.
- Second salary in household: equals one, zero otherwise.
- Son, daughter or other position different from the above: equals one, zero otherwise.

[25] Defined as having social security insurance registration, called *Seguro Social* and ISSSTE in Mexico.

Civil Status

- Single: equals one, zero otherwise.
- Married or 'free union'; equals one, zero otherwise.
- Divorced or widow: equals one, zero otherwise.

Education

- Desc1: Incomplete primary equals one, zero otherwise.
- Desc2: Complete primary school and incomplete secondary education equals. one, zero otherwise.
- Desc3: Post-primary courses equals one, zero otherwise.
- Desc4. Incomplete secondary school education equals one, zero otherwise.
- Desc5: Complete secondary education equals one, zero otherwise.
- Desc6: Incomplete post-secondary school training courses equals one, zero. otherwise.
- Desc7: Complete post-secondary school training courses equals one, zero. otherwise.
- Desc8: Incomplete high school education equals one, zero otherwise.
- Desc9: Complete high school education equals one, zero otherwise.
- Desc10: Education above the previous one equals one, zero otherwise.

Occupation in previous job

- Ocu1: Technician equals one, zero otherwise.
- Ocu2: Agricultural activities equals one, zero otherwise.
- Ocu3: Handicraft and repairing activities equals one, zero otherwise.
- Ocu4: Fix machinery operator equals one, zero otherwise.
- Ocu5: Assistant in repairing and maintenance activities equals one, zero. otherwise.
- Ocu6: Drivers and assistant of machinery handling equals one, zero otherwise.

- Ocu7: Administrative activities equals one, zero otherwise.
- Ocu8: Trade and selling activities equals one, zero otherwise.
- Ocu9: Personal services in established places equals one, zero otherwise.
- Ocu10: Domestic services equals one, zero otherwise.

Table A.1
Supplement to tables 5 and 6
The impact of the school-based training modality
Estimated parameters of proportional hazard functions

Variables	*Men*			*Women*	
	h_{u1}	h_e	h_{u2}	h_{u1}	h_e
Desc2	0.74 (-2.59)	2.31 (3.99)	0.87 (-0.44)	1.51 (1.35)	1.40 (0.53)
Desc3	0.47 (-2.16)	0.77 (-0.26)	NA	0.58 (-1.16)	3.58 (1.34)
Desc4	0.80 (-1.92)	2.70 (4.78)	0.80 (-0.71)	1.65 (1.43)	5.74 (2.62)
Desc5	0.76 (-2.53)	1.72 (2.61)	1.41 (1.12)	1.23 (0.64)	0.87 (-0.23)
Desc6	0.26 (-6.62)	2.29 (2.56)	1.32 (0.58)	1.89 (1.05)	1.78 (0.62)
Desc7	0.61 (-2.56)	2.03 (2.40)	1.26 (0.59)	1.15 (0.42)	0.43 (-1.32)
Desc8	0.75 (-2.26)	2.36 (3.80)	1.39 (1.01)	1.49 (0.98)	0.63 (-0.58)
Desc9	0.62 (-3.69)	2.22 (3.56)	0.83 (-0.54)	0.61 (-1.19)	1.72 (0.69)
Desc10	0.62 (-3.25)	1.13 (0.46)	0.38 (-2.33)	0.47 (-1.69)	0.61 (-0.40)
Ocu1	1.13 (0.91)	1.43 (2.09)	0.74 (-0.96)	0.86 (-0.32)	NA
Ocu2	0.61 (-3.10)	NA	NA	0.99 (-0.01)	NA
Ocu3	0.94 (-0.75)	1.50 (3.66)	0.91 (-0.56)	1.23 (0.83)	1.08 (0.18)

Table A.1
(*continued*)

Variables	*Men*			*Women*	
	h_{u1}	h_e	h_{u2}	h_{u1}	h_e
Ocu4	1.00 (0.01)	1.54 (2.97)	1.80 (2.98)	1.07 (0.25)	3.12 (2.56)
Ocu5	0.63 (-4.91)	2.32 (7.36)	1.59 (2.95)	0.57 (-1.71)	0.09 (-2.99)
Ocu6	0.88 (-1.02)	NA	NA	0.24 (-1.34)	NA
Ocu7	0.90 (-1.01)	0.64 (-2.58)	0.73 (-1.25)	0.65 (-1.96)	2.44 (2.32)
Ocu8	0.97 (-0.33)	1.31 (1.98)	1.25 (1.21)	0.65 (-1.86)	3.29 (3.21)
Ocu9	0.98 (-0.19)	2.42 (6.23)	1.17 (0.82)	0.33 (-4.54)	0.70 (-0.73)
Ocu10	0.87 (-0.50)	NA	NA	0.25 (-0.82)	1.66 (0.94)

Table A.2
Supplement to table 7
The impact of mixed-based training modality
Estimated parameters of proportional hazard functions

Variables	*Men*		*Women*	
	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$
Desc4	1.69 (-1.75)	1.52 (-0.99)	4.96 (3.37)	9.73 (2.75)
Desc5&6	1.52 (-1.57)	1.14 -0.33	1.98 (1.59)	5.92 (2.12)
Desc7	0.42 (-1.02)	0.97 (-0.03)	1.02 (0.04)	50.65 (3.46)
Desc8	2.03 (1.63)	0.99 (-0.02)	0.67 (-0.61)	52.31 (3.29)

Table A.2
(continued)

Variables	*Men*		*Women*	
	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$	h_{u1} $\exp(\beta_i)$	h_e $\exp(\beta_i)$
Desc9	1.62 (1.15)	1.36 (-0.6)	0.49 (-0.99)	2.43 (0.82)
Desc10	0.83 (-0.28)	1.71 (0.48)	1.60 (0.50)	162.05 (2.30)
Ocu1	NA	NA	1.37 (0.40)	0.01 (-2.25)
Ocu2	NA	NA	0.33 (-1.20)	NA
Ocu3	1.26 (0.74)	0.97 (-0.06)	0.56 (-1.05)	0.93 (-0.08)
Ocu4	2.11 (1.93)	0.80 (-0.39)	0.77 (-0.46)	5.95 (1.90)
Ocu5	0.69 (-1.18)	1.49 (0.87)	0.29 (-2.09)	4.42 (1.41)
Ocu7	1.10 (0.26)	0.37 (-1.69)	0.55 (-1.10)	5.07 (1.77)
Ocu8	1.68 (1.32)	1.74 (1.11)	0.46 (-1.48)	12.88 (2.81)
Ocu9	NA	NA	0.21 (-2.80)	8.79 (0)
Ocu10	1.54 (1.09)	4.48 (2.77)	0.72 (-0.58)	9.62 (1.96)

The matching procedure

In view of the large number of pre-treatment observable characteristics available to pair members of participant and comparison groups, we applied the propensity score method variant of matching (Rosenbaum and Rubin (1983)). This variant has the advantage of reducing the dimensionality of the matching problem down to matching on one scalar, while considering the importance of all pretreatment variables included in the analysis. This scalar is the propensity score, $P(X)$, defined as the probability of participation in the program conditional on pretreatment variables. The propensity score for participants and non-participants was estimated with logit models. The predictor variables included in these models were gender, age, family position, education and civil status, as well as: *a*)the time spent without a job before they started their training; *b*)the characteristics of his/her previous job according to whether it was in formal or informal sector, whether it was part or full time and if the person was self-employed or wage earner; *c*) reasons why the previous job was left –marriage, care of children or relative, market reasons, unsatisfied with the job and to study; *d*) geographic zone where individuals were located, and *e*) ten different types of occupation in their last job.

To match individuals we followed a *criterium* that required first, to be the same sex and second that the absolute differences in their propensity score values be no larger than .01. When there was more than one control candidate for a trainee, the matched person was randomly selected among non-participants fulfilling the *criterium*. Following this *criterium*, the number of trainees that could be included in our analysis was 89.5% men and 86.3% women, implying no significant "wastage" of information while having no differences in the support of the distribution.

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CENTRO DE ESTUDIOS ECONÓMICOS

In his prize-winning monograph, Angel Calderon, a leading Mexican microeconomist and microeconometrician, uses state of the art methods to study the dynamics of the Mexican labor market.

In two well executed essays, Calderon examines the nature of unemployment in the Mexican labor market and the effectiveness of a training program for the unemployed that was implemented in Mexico in 1994.

His first essay explores the important topic of segmentation of the Mexican labor market and the role of informality in explaining Mexican labor market dynamics. He presents evidence that a sizeable portion of the Mexican labor market excludes individuals who seek employment in it, but cannot attain it. He discusses the search strategies used by the unemployed and makes recommendations for improving labor market efficiency.

He shows that the labor market rigidities induced by Mexican law and regulation have serious consequences in creating and maintaining a substantial informal sector. Workers in the informal sector find it is difficult to leave informality once they enter it. Strategies that target those in the informal sector to transit to the formal sector might be very effective. His analysis suggests that it will be profitable to dismantle Mexico's rigid labor codes to free up its labor market and make it more fluid.

The second essay in this volume is a sophisticated evaluation of a training program designed to move Mexican workers out of unemployment. He extends the conventional approach to program evaluation that focuses mainly on the impact of programs on trainee wages and unemployment to look at the impact of the program on trainee weeks of employment. He presents a much more complete evaluation of the program and demonstrates its positive impact. His analysis reverses conclusions from previous analyses about the effectiveness of the program.

His well crafted and well exposited research deserves careful attention by analysts and policy makers. The methodology developed in this work should be applied more widely to study the performance and problems of Mexican labor markets

James J. Heckman
2000 Nobel Prize Winner in Economic Sciences and Professor of Economics at the University of Chicago

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