

Mobility in the Urban Labor Market: a panel data analysis for Mexico

Xiaodong Gong, Arthur van Soest * & Elizabeth Villagomez †

Abstract

We analyze mobility in urban Mexico between three labor market states: working in the formal sector, working in the informal sector, and not working. We use a dynamic multinomial logit panel data model with random effects, explaining the labor market state of each individual during each time period. The data is drawn from Mexico's Urban Employment Survey, a quarterly household survey for urban Mexico. Two separate five-wave panels are used: the first covering a period of rapid economic growth (1992 – 1993), the second a period of recession after the Peso crisis (1994 – 1995).

Our main results are in line with the theory that formal sector jobs are superior to informal sector jobs and that working in the informal sector is a temporary state for those who cannot find a formal sector job and cannot afford not to work. Entry and exit rates for the formal sector are lower than for the informal sector. The probability of formal sector employment strongly increases with education level. For men, it is easier to enter the formal sector from the non-working state than from the informal sector. The probability of working in the informal sector decreases with the level of income of other family members, while the probability of not working increases with it.

JEL CODES: C23, C25, J60, R23

KEYWORDS: informal sector work, mobility, panel data, Mexico

*Tilburg University, P.O. Box 90153, 5000LE, Tilburg, the Netherlands, e-mail: x.gong@kub.nl, avas@kub.nl.

†Fundacion Tomillo, Centro de Estudios Economicos.

The authors thank Manuel Arellano, Bas Donkers, Magnus Lofstrom, Christian Dustmann, Hidehiko Ichimura and other participants of seminars at Tilburg University, Fundacion Tomillo, ZEW and IZA, and of the ENTER Jamboree at UCL for useful comments.

1 Introduction

Urban labor markets in developing countries are generally characterized by the presence of a large informal sector. While formal sector employment is subject to regulation, social premiums and taxation, with wages paid on a regular basis, and explicit contracts between employers and employees, the informal sector is not subject to institutional regulations and mainly consists of small firms and self-employment.

The segmentation of the labor market into a formal and an informal sector has been analyzed extensively during the last two decades. Two competing points of view on the role of the informal sector exist. The traditional staging hypothesis in the theoretical work of Fields (1975) is that formal sector employment is rationed. Those who cannot obtain a formal sector job either search from unemployment, or, if they cannot afford to be unemployed, work in the informal sector. Thus informal sector workers have secondary jobs, and would be better off with a primary job in the formal sector. In this view, the informal sector functions as an intermediary buffer sector between not working and the formal sector.

The other view sees the two sectors as symmetric and competitive. The formal and informal sector have different production functions, and heterogeneity among workers implies that some are more productive in one sector while others have larger productivity in the other sector. Under the assumption that unrestricted workers choose the sector where they are most productive and can earn the highest wage, this model can be tested using cross-section data on individual workers' sector choice and wages, see Heckman and Sedlacek (1985). Magnac (1991) applies an extension of this model – which also accounts for the state of not working – to married women in urban areas in Columbia. He finds that this model cannot be rejected, and concludes that the labor market is in a ‘weakly competitive equilibrium.’

Other empirical evidence on sector choice and wage differentials between formal and informal sector is mixed. For example, Strassmann (1987) found that 71 percent of home workers in Lima would require a considerable financial incentive to move to the formal sector (see also Thomas, 1992). Pradhan and Van Soest (1995), using data for urban Bolivia, compare reduced form models for sector choice in which sectors are ordered with models in which sectors are not ordered, and find that the ordered model performs better for men but not for women. Using the same data in a more structural model, Pradhan and van Soest (1997) find that wage differentials between formal and informal sector tend to be negative rather than positive, and that non-monetary job characteristics (such as job stability, social security, health care access, etc.) are needed to explain why most people prefer formal sector jobs. Studies looking at wage differentials for various countries –with mixed results– are reported by Pradhan and van Soest (1995), for example. These existing studies are based on cross-section data.

Our study explores the role of the informal sector from a dynamic perspective, using quarterly panel data for five large cities in Mexico. This seems particularly useful since the staging hypothesis model of Fields (1975) uses a dynamic setting, and has impli-

cations for the mobility between sectors. We study the mobility patterns among three different labor market states which are formal sector employment, informal sector work, and not working; and analyze how these patterns vary across groups with different characteristics and family resources, and between periods of economic growth or recession. We also discuss the extent to which our findings support either the Fields (1975) model or the weakly competitive equilibrium view.

Obviously, both views are stylized, and the actual labor market will share features of both. Still, many of our findings are in line with the staging hypothesis of Fields (1975). Entry rates into the formal sector are lower than into the informal sector for the low educated nonworkers, showing that entry into the formal sector is more difficult for them. The probability of formal sector employment strongly increases with education level. For men, it is easier to enter the formal sector from the non-working state than from the informal sector. Such a result cannot be found for women, since most women who do not work, are not looking for work either, implying that the transition rates from non-working to formal and informal sector work are low. The probability of working in the informal sector decreases with the level of income of other family members, while other family income increases the probability of not working. This confirms the view that only those who can afford it do not work.

The remainder of the paper is organized as follows. Section 2 provides some background information regarding the Mexican urban labor market and describes the data, which are drawn from the Mexico Urban Employment Survey. Two separate panel data sets are available to us, each of which consists of five quarterly waves. The first runs from the first quarter of 1992 until the first quarter of 1993, a period of steady economic growth. The second runs from the last quarter of 1994 till the last quarter of 1995 – a period of recession following the so-called Peso crisis. We present descriptive statistics on the size of the three sectors in each wave, and on transition rates. We also present some illustrating figures on wage levels in formal and informal sectors, although wages will not be incorporated explicitly in our econometric model.

The econometric model is discussed in Section 3. We use a reduced form dynamic multinomial logit model for panel data with random effects, explaining the labor market state of each individual in each time period. The model is a variation of the first-order Markov models proposed in Heckman (1981a), where ‘true’ structural state dependence and heterogeneity are distinguished by including dummies for the one period lagged labor market state, as well as unobserved individual random effects. We compare the results of a model in which the lagged dependent variables are interacted with exogenous variables with those of a parsimonious model without interactions. The initial condition problem associated with this kind of model is treated following the procedure proposed by Heckman (1981b).

The estimation results are discussed in Section 4. Moreover, to interpret the meaning of the parameter estimates, we use the model to simulate transition probabilities for groups with various background characteristics. Conclusions are drawn in section 5.

2 Background information on the labor market and Data

2.1 Mexico's Labor Market

After going through a serious and painful economic adjustment in the wake of the “debt crisis” in the 1980's, Mexico enjoyed a period of economic growth. From 1989 to 1994, average GDP growth was about 3.9 percent per year.¹ Growth ended abruptly in 1995, when GDP fell by 6.2 percent in the aftermath of the so-called “Peso Crisis”. The economy recovered rapidly in 1996 with GDP increasing by 5.9 percent.

A typical feature of the Mexican labor market is its low open unemployment rates, despite a continuously growing labor force. Since the 1980's, the official urban unemployment rate kept falling, to 2.6 percent in 1991, and it remained below 4 percent until 1994 (see Fleck and Sorrentino, 1994). It increased in 1995 due to the crisis, but even at the worst point in 1995, it was still below 7 percent. In 1997 and 1998, it fell back below 4 percent and 3 percent, respectively (see OECD, Main Economic Indicators, May 1999). At the same time, Mexico's labor force grew rapidly, with an annual rate of about 2.9 percent in the 1990's. An explanation for the low unemployment rate could be that official open unemployment does not include all those who would be counted as unemployed by Western concepts, such as underemployed workers. As shown by Fleck and Sorrentino (1994), however, the unemployment rate is still relatively low according to Western standards after this is adjusted for.

Another explanation for this is the presence of an informal labor market, where a large number of individuals have some marginal job. Two arguments for this second explanation can be given. On the one hand, Mexico's formal sector is characterized by extensive labor market regulations. Mexican Federal Labor Law (FLL) governs virtually every aspect of labor relations, such as minimum wages, limits on working hours, overtime pay, profit sharing, etc. It was especially designed to protect the individual employees' employment security (see Hollon, 1996, and Zelek and de la Vega, 1992), and includes rules for termination of employment, including obligations of severance payments. In addition, the government places health and safety requirements on firms. Hiring would be prohibitively costly for many small firms, particularly those who are not officially registered, if they were to fulfil all the requirements. On the other hand, Mexico has no unemployment compensation, so that individuals without (formal) work are often forced into “marginal activities”, such as street vending, etc. Those who are actually unemployed and do not undertake such activities are then those who can afford to search (See Fleck and Sorrentino, 1994). This is in line with the staging hypothesis which views the informal sector as consisting of secondary jobs.

Mexico has the lowest labor costs per worker of all OECD countries. Its average labor costs are less than 25% of those in Germany and less than 30% of those in the US

¹The figures are based on World Development Indicators, 1997.

(OECD, 1998). The main reasons are low gross wages and the absence of income taxes. Social security contributions are lower than OECD average but higher than in countries such as Japan, the UK or Spain.

2.2 Data

The data used in the analysis were drawn from Mexico's Urban Employment Survey (*Encuesta Nacional de Empleo Urbano*), conducted by *Instituto Nacional de Estadística, Geografía e Informática* (INEGI, *i.e.* Mexican Statistical Institute). This is a rotating panel drawn in 32 Mexican cities, and it is the only quarterly household panel survey in Mexico. For our analysis, we use the data for five Mexican cities: Mexico City, Guadalajara, Monterrey, Tijuana, and Ciudad-Juarez. These five cities cover 60 percent of urban employment in Mexico. In the border towns Tijuana and Ciudad-Juarez the in-bond industries concentrate. Mexico City, Guadalajara and Monterrey represent about a quarter of the entire population of Mexico, and half of the population of cities with more than 100,000 inhabitants. Moreover, Guadalajara is the city with the largest share of informal workers (See Villagomez, 1998).

Our first panel covers a period of economic growth: the first quarter of 1992 until the first quarter of 1993. The second panel, from the last quarter of 1994 until the last quarter of 1995, covers the recession after the Peso crisis. The survey provides detailed information on the economic activities of all the household members older than twelve years of age, such as employment status, employment conditions, working hours, labor income, characteristics of the workplace, etc., but no information on nonlabor income. Data from the survey have been used to calculate the official open unemployment rates of Mexico. They have also been used by, for example, Fleck & Sorrentino (1994) for the analysis of unemployment in urban Mexico, and by Villagomez (1996,1998) and Calderón-Madrid (1999) for studies of labor market segmentation and labor market mobility.

The 1992 panel consists about 2500 households in each wave, and the 1995 panel has about 2700 households per wave. From the two panels, four separate unbalanced panels of men and women were created. Only those individuals who are present in at least two consecutive quarters were selected. We only selected men and women who are either the head of the household or the spouse of the head of the household, who are younger than 65 years of age, and who are not full time students. In this way we retained 1691 males and 1907 females for the 1992 panel, and 1673 males and 1923 females for the 1995 panel. However, 269 males and 627 females in the 1992 panel, and 298 males and 636 females in the 1995 panel were excluded because information on other family members' income was missing. Moreover, 18 males and 82 females in the 1992 panel, and 11 males and 79 females in the 1995 panel were left out because they are unpaid family workers (see below). This gave the final samples we work with. For the 1992 panel, we have 1404 men and 1198 women. For the 1995 panel, we have 1364 men and 1208 women. In the 1992 panel, about 64% of the observations is present in all the five waves, and

about 12% in only two waves; while in the 1995 panel, about 75% of the observations is present in all the five waves, and 7.7% in only two waves. The explanation of the variables used in the analysis and sample statistics are presented in Table A1 and Table A2 of the appendix.

Until now, we have not precisely defined the distinction between formal and informal sector jobs. According to the 1972 ILO Employment mission to Kenya, informality is defined as a “way of doing things characterized by: (1) ease of entry, (2) reliance on indigenous resources, (3) family ownership of resources, (4) small scale of operation, (5) labor intensive and adapted technology, (6) skill acquired outside of the formal school system, and (7) unregulated and competitive markets” (c.f. ILO, 1972). This definition, however, has to be made more precise to be used empirically. Some authors have emphasized the small scale of informal activities, and use a definition based upon size. Others have used survey information on the nature of the employment relation (Magnac, 1991, Pradhan and van Soest, 1995, 1997). A third definition which seems less common in the international literature, is based upon whether social security premiums are paid (see Calderón-Madrid, 1999, and Martin, 1999). We compare the classifications according to these three definitions. In the economic models, we will use a definition based upon size as the benchmark, but also present some results using a definition based upon occupational status.

For the benchmark (‘size’) definition, an individual is defined as working in the informal sector if he or she is an employer or employee in a setup with fewer than six workers, and is neither a professional nor an unpaid family worker. Professionals (lawyers, doctors, etc.; about 5% of men and 0.5% of women) are categorized as formal sector workers, together with all those in enterprises of more than five workers. Unpaid family workers could neither be categorized as workers nor as non-workers, and are therefore deleted from the sample.

The alternative (‘job type’) definition is mainly based on a survey question which distinguishes various sorts of jobs. Those who “work for their own account,” piece-workers, and those who report to be the head of a firm with zero employees, are categorized as informal. Those who work for a fixed wage, cooperative workers, employers (with at least one employee) and independent professionals, are categorized as formal. Unpaid family workers are again deleted from the sample.

The two definitions do not lead to the same classification. For the first panel, for example, 57.4% of working men are in the formal sector according to both definitions, 12.2% are formal according to the job type definition, but informal according to the size definition, 5.0% are formal according to the size definition and informal according to the job type definition, and 25.4% are informal according to both definitions. In particular, many workers are salaried employees in firms with less than six employees, and are classified as informal according to the size definition only. For the first panel of men, for example, salaried workers are about 63.3% of all workers, and about 13.8% of the salaried workers are classified as informal workers according to the ‘size’ definition,

but all of them would be classified as formal workers according to ‘job type’ definition. Moreover, piece workers who would be classified as informal workers according to the ‘job type’ definition are about 8.2% of all the workers, but about 60.3% of them are classified as formal workers according to the ‘size’ definition. For the other panel and for women, a similar degree of overlap between the two definitions is found.

To understand the classifications more precisely, we cross-tabulated in Table 1 the results according to both definitions given above with the coverage of social security services. Compulsory social security includes ‘ISSSTE’ and ‘IMSS’, which are the social security institutions in Mexico. By law, an employee in an officially registered firm should be covered by either of the two. They cover a range of services for those who pay into either of the two systems (medical, sport facilities, funeral services, child-care services for working women, etc.). ISSSTE covers public sector employees, and IMSS covers the private sector. Until recently, these two systems also involved pensions, but this has recently been reformed. Other social security services than ‘ISSSTE’ or ‘IMSS’ include, for example, private and voluntary insurances. Most of the 54.7% workers covered by the social security services are classified as formal workers by both of the two definitions, and this is similar for the two definitions. However, about 26.4% and 40.2% of the workers who are not covered by the social security services are classified as formal workers according to firm size and job-type definition, respectively. Thus social security coverage corresponds better to the firm size classification than to the job type classification. This also makes us lean towards the firm-size definition. The reason that we do not use the coverage of social security services as the criterion is that it seems too restrictive and does not correspond to definitions used in the international literature. The formal sector implies more than having access to social security services, for example, severance payments, etc.. Some workers may only enjoy some part of their rights regulated by the labor institutions.

Table 1. Social security and classification into formal and informal jobs (%)

Social security	Firm-size			Job-type		
	formal	informal	total	formal	informal	total
none	11.98	33.35	45.33	18.24	27.09	45.33
compulsory	45.03	3.36	48.39	45.62	2.77	48.39
other	5.43	0.85	6.28	5.79	0.49	6.28
total	62.44	37.56	100	69.65	30.35	100

Because of the problems with measuring open unemployment and the small numbers of people classifying themselves as unemployed, we do not distinguish unemployment as a separate labor market state. We thus merge the unemployed with other non-workers. Table 2 shows how the percentages of formal sector workers, the informal sector workers, and nonworkers evolve over time. It is based upon the size definition. For men in our sample, the formal sector and informal sector workers represent about 60% and 35%

of the labor force, respectively. During 1995, the formal sector share falls from 61% to 55%, illustrating the recession. On the other hand, the informal sector increases from 33% to 36%. The number of men without work is small, but larger in 1995 than in 1992. The employment rate of women in the sample has increased from 1992 to 1995, but remains quite low. During 1992, about 18% of women worked in the formal sector. This increased to about 21% in 1995. The percentage in the informal sector is smaller. Still, the number of informal sector workers as a percentage of all workers, is larger for women than for men.

The analogue of Table 2 using the job type definition of the informal sector is presented in Table A4 in the appendix. It has smaller numbers of informal sector workers, in line with the comparison for the first quarter discussed above. The pattern over time and the relative differences between men and women, however, are similar to those in Table 2.

Table 2. Sample percentages in three labor market states

Quarter	92.1	92.2	92.3	92.4	93.1	94.4	95.1	95.2	95.3	95.4
Males										
Formal	57.9	56.4	58.8	58.6	57.7	60.9	59.9	56.4	55.0	55.2
Informal	35.8	35.4	34.6	34.1	34.2	33.1	32.4	34.8	35.3	36.4
Nonempl.	6.4	8.2	6.6	7.3	8.1	5.9	7.7	8.8	9.8	8.4
Females										
Formal	17.6	17.6	17.8	18.4	17.8	21.9	20.6	20.8	21.1	19.6
Informal	13.6	12.5	12.1	12.5	12.6	13.8	13.9	12.7	12.1	12.8
Nonempl.	68.8	70.0	70.1	69.0	69.6	64.4	65.5	66.6	66.7	67.6

As a first illustration of the difference between formal and informal sector, Figures 1 and 2 compare real wages in the two sectors (using the size definition).² We do this separately for those of the middle and higher and those of the lower education levels (see Table A1). For men and women who received middle and higher education, the averages of the formal sector log wages are always clearly larger than those in the informal sector. The sample standard deviations of the log wages are similar. The higher average wage in the formal sector seems to support the staging hypothesis. For the individuals with lower education level, however, a very different picture emerges. The differences in the means are small, and the standard deviation in the formal sector is smaller than in the informal sector.³

In Table 3, the sample probabilities of individuals' transitions among the three labor market states are presented. These are based upon the firm size classification. For both males and females, the nonworkers have a larger probability to find an informal job

²The nominal wages are computed from reported monthly income divided by actual working hours, and the real wages are obtained from the nominal wages using IMF CPI as the deflator (Source: Data Stream).

³Quantitatively similar results are obtained if monthly earnings are used instead of hourly rates.

than to find a formal job, and for males, this difference increases during the recession. Moreover, the proportion of male nonworkers who remain inactive in the next quarter is higher in the economic boom than in the recession. As shown in the table, the probabilities of remaining in the formal sector are larger than those of remaining in the informal sector, suggesting that the exit rates for the formal sector are lower than for the informal sector. This does not necessarily mean, however, that jobs in the formal sector are more stable than jobs in the informal sector. It could be the case that job separations for formal and informal sector jobs are equally likely. The difference in sector exit rates could then be due to the fact that the probability that someone who leaves a job in the formal sector finds another formal sector job, is larger than the probability that someone who leaves an informal sector job, goes to another informal sector job. The mere difference in size between the sectors might be a plausible explanation for this, particularly for men. Since the data do not provide information on whether people change jobs or not, we are unable to compare job mobility in the two sectors.

The sample probabilities of transitions according to the job type definition are presented in the Tables A5. The transition rates into the formal sector are larger than those according to the “firm-size” definition, but the general patterns of the transitions probabilities are not very different. The size of mobility among the three states is quite large according to both definitions. For example, around 12% of formal sector and more than 20% of informal sector male workers in 1992 leave their sector in the next quarter according to the firm size definition. According to the job type definition, these two figures are about 14% and 29%, respectively.

Table 3. Sample probabilities of transitions

$t - 1$	$t = 2$			$t = 3$			$t = 4$			$t = 5$		
	Form.	Infor.	Noem.	Form.	Infor.	Noem.	Form.	Infor.	Noem.	Form.	Infor.	Noem.
<u>Men 92</u>												
Form.	0.874	0.088	0.038	0.884	0.098	0.018	0.880	0.093	0.027	0.871	0.099	0.030
Infor.	0.142	0.796	0.061	0.175	0.765	0.059	0.158	0.772	0.070	0.134	0.797	0.068
Noem.	0.100	0.271	0.629	0.200	0.250	0.550	0.227	0.213	0.560	0.183	0.183	0.634
<u>Men 95</u>												
Form.	0.873	0.095	0.033	0.841	0.106	0.053	0.864	0.083	0.053	0.877	0.084	0.038
Infor.	0.167	0.758	0.076	0.133	0.787	0.080	0.128	0.802	0.070	0.139	0.801	0.060
Noem.	0.203	0.261	0.536	0.155	0.393	0.452	0.186	0.320	0.495	0.189	0.369	0.441
<u>Women 92</u>												
Form.	0.769	0.036	0.195	0.810	0.033	0.158	0.823	0.059	0.118	0.826	0.047	0.128
Infor.	0.062	0.608	0.331	0.083	0.598	0.318	0.062	0.628	0.310	0.040	0.640	0.320
Noem.	0.033	0.052	0.915	0.033	0.056	0.911	0.041	0.052	0.908	0.035	0.050	0.915
<u>Women 95</u>												
Form.	0.817	0.052	0.131	0.863	0.048	0.088	0.853	0.022	0.124	0.813	0.064	0.123
Infor.	0.056	0.681	0.264	0.058	0.639	0.303	0.064	0.636	0.300	0.063	0.659	0.278
Noem.	0.019	0.052	0.929	0.032	0.047	0.922	0.040	0.051	0.909	0.027	0.053	0.920

Explanation: number of transitions from labour market state in $t - 1$ (row) to labour market state in t (column), as a percentage of number of people in labour market in $t - 1$ (row). For example, 14.2% of all men who work in the informal sector at time of the first wave of the 92 panel work in the formal sector three months later.

3 Model and Estimation Method

To explain the labor market state of each individual in each quarter, we use a dynamic multinomial logit panel data model with random effects. This model is similar to the first-order Markov model proposed in Heckman (1981a). The model distinguishes between ‘true’ structural state dependence and unobserved heterogeneity by including lagged state dummies as explanatory variables and individual effects to control for the unobserved characteristics. The individual effects are assumed to be independent of the observed characteristics (and therefore called random effects) and to follow a multivariate normal distribution. The model is reduced form in that it does not take into account the wage effect directly. Instead, the impact of wages is accounted for indirectly by including education and age variables. The initial condition problem associated with applying this model to a short panel, is treated as in Heckman (1981b).

More precisely, assume individual i ($= 1, \dots, n$) can be in any of J possible labor market states at time t . Throughout the paper, we will use $J=3$: working in the formal sector ($j = 1$), working in the informal sector ($j = 2$), and not working ($j = 3$). The “utility” of state j ($j = 1, \dots, J$) in time period $t > 1$ is specified as

$$V(i, j, t) = X'_{it}\beta_j + Z'_{it}\gamma_j + \alpha_{ij} + \epsilon_{ijt}, \quad (1)$$

where X_{it} is a vector of explanatory variables which includes age, educational dummies, family composition, time dummies, etc.. Z_{it} is a vector of dummy variables indicating the lagged labor market state, and of interactions of these dummies with X_{it} . Here we use two dummies for informal sector and not working, the formal sector is taken as the reference state. The vectors β_j and γ_j are parameters to be estimated. α_{ij} is a random effect reflecting time constant unobserved heterogeneity. To identify the model, β_1 , γ_1 , and α_{i1} are normalized to 0. The ϵ_{ijt} are i.i.d. error terms. They are assumed to be independent of the X_{it} and α_{ij} , and are assumed to follow a Type I extreme value distribution. Hence, the probability for individual i to be in state j at time $t > 1$, given characteristics X_{it} , random effects α_{ij} ’s and the lagged state dummies, can be written as

$$P(j | X_{it}, Z_{it}, \alpha_{i1}, \dots, \alpha_{iJ}) = \frac{\exp(X'_{it}\beta_j + Z'_{it}\gamma_j + \alpha_{ij})}{\sum_{s=1}^J \exp(X'_{it}\beta_s + Z'_{it}\gamma_s + \alpha_{is})}, \quad (2)$$

Let $\boldsymbol{\alpha}_i \equiv (\alpha_{i2}, \dots, \alpha_{iJ})'$. The $\boldsymbol{\alpha}_i$ are assumed to follow a multivariate normal distribution.⁴ In other words, the α_{ij} are specified as linear combinations of $J-1$ independent $N(0, 1)$ variables:

$$\boldsymbol{\alpha}_i = \mathbf{A}\boldsymbol{\eta}_i, \quad \text{with } \boldsymbol{\eta}_i \sim N_{J-1}(0, I_{J-1}) \quad (3)$$

where \mathbf{A} is a $J-1 \times J-1$ lower triangular parameter matrix to be estimated. The covariance matrix of $\boldsymbol{\alpha}_i$ is then given by $\Sigma_\alpha = \mathbf{A}\mathbf{A}'$.

⁴We also experimented with discrete distributions with a finite number of mass points, but this did not lead to larger likelihood values and gave convergence problems for more than two or three mass points.

Due to the presence of the lagged dependent variables in Z_{it} , an initial conditions problem arises. This can be dealt with in the same way as in Heckman (1981b): for time $t = 1$, a static multinomial logit model is used, with different slope parameters and not including Z_{it} . This model can be seen as a linear approximation to the reduced form that would be obtained if the lagged dependent variables were replaced by their specifications according to the dynamic model for periods earlier than $t = 1$. Although this approximation is not exact due to the nonlinear nature of the model, Heckman (1981b) reports Monte Carlo results showing that this procedure performs quite well for a dynamic panel data binary choice model, and the approximation leads to a small asymptotic bias only. The specification of $V(i, j, 1)$ is as follows:

$$V(i, j, 1) = X'_{i1}\pi_j + \theta_{ij} + \epsilon_{ij1}, \quad (4)$$

where π_j is a vector of parameters and θ_{ij} is the random effect; As before, the errors ϵ_{ij1} are assumed to be independent of all X_{it} and α_{ij} (and θ_{ij}), and of all ϵ_{ijt} in other time periods t , and are assumed to be i.i.d. with a Type I extreme value distribution. The probability for individual i to be in state j ($j = 1, \dots, J$) at time $t = 1$, given X_{i1} and the random effects $\boldsymbol{\theta}_i = \theta_{i2}, \dots, \theta_{iJ}$, can thus be written as

$$P_1(j | X_{i1}, \boldsymbol{\theta}_i) = \frac{\exp(X'_{i1}\pi_j + \theta_{ij})}{\sum_{s=1}^J \exp(X'_{i1}\pi_s + \theta_{is})} \quad (5)$$

Again, π_1 and θ_{i1} are normalized to 0. The reduced form interpretation of (4) implies that the random effects θ_{ij} are induced by unobserved heterogeneity in (1), so that they will be functions of $\boldsymbol{\alpha}_i$. We therefore assume that $\boldsymbol{\theta}_i = (\theta_{i2}, \dots, \theta_{iJ})'$ is given by

$$\boldsymbol{\theta}_i = \mathbf{C}\boldsymbol{\alpha}_i = \mathbf{B}\boldsymbol{\eta}_i \quad (6)$$

where \mathbf{B} is a $J - 1 \times J - 1$ lower triangular parameter matrix to be estimated. The covariance matrix of $\boldsymbol{\theta}_i$ (Σ_θ) is thus given by $\mathbf{B}\mathbf{B}'$.

The model can be estimated by Maximum Likelihood. If the random effects $\boldsymbol{\eta}_i$ (or $\boldsymbol{\alpha}_i$ and $\boldsymbol{\theta}_i$) were observed, the likelihood contribution of individual i with observed states j_1, \dots, j_T would be given by

$$L_i(\boldsymbol{\eta}_i) = P_1(j_1 | X_{i1}, \boldsymbol{\theta}_i) P(j_2 | X_{i2}, Z_{i2}, \boldsymbol{\alpha}_i) \cdots P(j_T | X_{iT}, Z_{iT}, \boldsymbol{\alpha}_i) \quad (7)$$

This is straightforward to compute, since it is a sequence of multinomial logit probabilities. Since the individual effects are not observed, however, the likelihood contribution will be given by the expected value of (7):

$$L_i = \underbrace{\int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty}}_{J-1} L_i(\boldsymbol{\eta}_i) \varphi(\boldsymbol{\eta}_i) d\eta_{i2} \cdots d\eta_{iJ}, \quad (8)$$

where $\varphi(\boldsymbol{\eta}_i)$ is the joint density function of $\boldsymbol{\eta}_i$. Computation of the likelihood contribution in (8) involves $J - 1$ dimensional integration. In our case, $J = 3$, and various

numerical techniques exist to approximate the integral. We will use a (Smooth) Simulated Maximum Likelihood approach, which also works for larger values of J . It is based upon the fact that (8) is the expected value of (7); the expected value is approximated by a simulated mean. For each individual, R values of $\boldsymbol{\eta}_i$ are drawn from $N_{J-1}(0, I_{J-1})$, and the average of the R likelihood values conditional on the drawn values of $\boldsymbol{\eta}_i$ are computed. The integral in (8) is thus replaced by

$$L_i^R = \frac{1}{R} \sum_{q=1}^R L_i(\boldsymbol{\eta}_i^q) \quad (9)$$

The resulting estimator is consistent if R tends to infinity with the number of observations (n). If $n^{1/2}/R \rightarrow 0$ and with independent draws across observations, the method is asymptotically equivalent to maximum likelihood, see Lee (1992) or Gourieroux and Monfort (1993), for example. In our empirical setting, we used $R = 30$. To check the sensitivity of the results for the choice of R , we also estimated the model for $R = 20$, and found little change in the results when we increased R from 20 to 30.

4 Results

Estimates

We estimated two models. The first is a parsimonious model in which the interactions between the lagged dependent variable and demographic variables, such as, age, education, and city dummies, are excluded. The other is the general model without this restriction and with all interactions. The models were estimated separately for the two panels, for both men and women. Likelihood ratio tests show that, at the 1% significance level, the null hypothesis of no interaction terms is rejected only for males of the 1992 panel.⁵ Hence, our further analysis will focus on the restricted model. We present some results of the unrestricted model for men of the 1992 panel in the appendix (Tables A9) for comparison.

Presented in Table 4 are the estimates of the dynamic equations in (1), for the restricted and unrestricted models, respectively. The estimates of the static reduced form equation (4) are reported in Table A3 of the appendix. A positive sign of the parameter β_j or γ_j ($j = 2, 3$) means that the corresponding variable has a positive impact on the probability to be in state j compared to the probability to be in the formal sector (the reference state). Most parameter estimates are similar for the two time periods. According to the restricted model, age plays a significant role in that the young and the elderly are more likely to be not employed. Compared to the ones

⁵The χ^2 statistics for men of 1992 panel, women of 1992 panel, men of 1995 panel, and women of 1995 panel, are 91.0, 42.6, 44.8, and 34.1, respectively. The 1% critical value for a χ^2 distribution with 28 degrees of freedom is 48.3.

who received lower education (both men and women), higher educated persons were less likely to be in the informal sector or to be not employed. For women, having younger children reduces the probability to work, both in the formal and the informal sector. The number of children does not affect the men’s behavior. The impact of these demographic variables is also in line with the common findings in the literature. The regional dummies are mostly insignificant for the 1992 panel, but for the 1995 panel, when the general market conditions were worse in most of the country, the picture changed. In the city of Guadalajara, where the informal sector was the largest, men were more likely to be in the informal sector or not employed than in Mexico City. Women in the border cities of Ciudad Juarez and Tijuana are less likely to be in the informal sector or to be not employed than those in Mexico City. An explanation may be that in the former two cities, many *Maquiladoras*⁶ (in-bond industries) whose main labor force are unskilled women are located (See Kopinak, 1995). These workers are classified as formal sector workers. The products of these industries are mainly exported to the U. S.. The 30% devaluated peso after the ‘Peso Crisis’ made Mexican labor cheaper and stimulated the activity and demand for labor in the in-bond industries.

For the 1992 panel, the coefficients of the variable ‘Othinc’ (income of other family members) corresponding to the state ‘Informal’ are significantly negative, which means that higher income of other family members decreased the probability of working in the informal sector. However, for the 1995 panel, although the signs are still negative, this is not significant anymore. This is the case for both men and women. In addition, for the 1995 panel, higher income from other family members increased the men’s probability of being not employed. In the boom of 1992, individuals with more sources of income could afford to search and could find desired (formal) jobs, but during the recession, when the number of (formal) jobs shrank, they could not find formal jobs as easily as before, and their probability of being not employed increased.

The positive signs of coefficients of the lagged dependent variables indicate that an individual who works in the informal sector is more likely to be not employed in the next quarter than a similar individual who held a formal sector job, and that a nonworker has a larger probability to enter the informal sector than a formal sector worker. The variances and the covariances of the random effects are in the last part of Table 4. The results show that the random effects always play a significant role and contribute more to the state choice than the idiosyncratic errors (which, by normalization, all have variance $\pi^2/6$). Moreover, the two individual heterogeneity terms are positively correlated.

Our findings with the unrestricted model are not very different. Taking into account the interaction effects, the overall profile does not change much, but the parameters (particularly the interaction terms) are estimated with less precision. In Table A6, we present the estimates of the unrestricted model for men of the 1992 panel. Only the interactions of lagged dependent variables with city dummies are included, because other interaction terms (including, perhaps surprisingly, interactions with education

⁶See Martin, (1999), for some institutional background information

level dummies) do not play a significant role. In 1992, compared to those in Mexico City, men in Tijuana, Ciudad-Juarez, or Guadalajara are less likely to have a formal sector job, but the informal sector workers in these cities are significantly more likely to find a formal sector job in the next quarter than in Mexico City, and the inactive individuals in the two border towns are also more likely to find a formal sector job in the next quarter. The dynamic effects in this model are not so easy to interpret. We will look at simulated transition probabilities in the next section.

Table 4. Estimates of the restricted model –dynamic equation

Param.	1992 Panel				1995 Panel			
	Men		Women		Men		Women	
	Infor.	Noem.	Infor.	Noem.	Infor.	Noem.	Infor.	Noem.
$\beta_j :$								
<i>Const.</i>	-0.513	-1.677	-4.816*	-2.164**	-1.845	0.095	-1.476	2.381**
<i>Age</i>	-0.033	-0.142*	0.140**	-0.129**	-0.007	-0.201*	-0.027	-0.174*
<i>Age2</i>	0.001	0.003*	-0.001	0.002*	0.000	0.003*	0.001	0.003*
<i>Child</i>	0.163	-0.173	0.157	0.545*	-0.094	-0.129	0.159	0.390*
<i>Adults</i>	-0.089	-0.008	0.093	0.087	0.172*	0.144*	0.140	0.022
<i>Medu</i>	-0.960*	-0.304	-1.199*	-0.967*	-1.427*	-1.071*	-1.634*	-1.152*
<i>Hedu</i>	-3.058*	-1.459*	-1.904*	-2.279*	-2.387*	-1.584*	-2.092*	-2.375*
<i>Othinc</i>	-0.040**	0.038	-0.073**	0.022	-0.011	0.050**	-0.053	0.059
<i>JuaTij</i>	0.016	0.176	-0.453**	0.134	-0.185	-0.368**	-0.586**	-0.534*
<i>Guada</i>	0.065	0.219	0.011	-0.089	0.763*	0.849*	0.119	0.126
<i>Mont.</i>	-0.193	-0.015	0.001	0.042	-0.466*	-0.360	0.420	0.195
<i>Nmar</i>	-0.149	1.395*	0.050	-1.958*	0.132	1.319*	-0.307	-1.949*
<i>T3</i>	-0.141	-0.401**	-0.140	-0.201	0.397*	0.452*	-0.379	-0.273
<i>T4</i>	-0.213	-0.225	-0.104	-0.270	0.409*	0.528*	-0.498**	-0.324
<i>T5</i>	-0.085	-0.072	-0.094	-0.154	0.414*	0.289	-0.136	-0.062
$\gamma_j :$								
<i>Infor._1</i>	1.238*	1.294*	3.901*	2.489*	1.437*	0.776*	2.322*	2.027*
<i>Noem._1</i>	1.161*	2.584*	2.856*	2.927*	1.738	2.081*	1.937*	3.492*
$\Sigma_\alpha :$								
σ_2^2	9.686*		1.412*		9.121*		6.400*	
σ_3^2	2.920*		3.489*		3.121*		3.762*	
σ_{23}	3.954*		0.610		4.517*		3.293*	

Notes:

* Significant at 5% level; ** significant at 10 % level.

Reference state: formal sector work

σ_j^2 : variance of α_{ij} , $j = 2, 3$; σ_{23} : covariance of α_{i2} and α_{i3}

“*Lowedu*”, “*T2*”, “*Mex. City*”, and “*Form._1*”, are the omitted control group dummies

Simulations

The simulations are conducted for the first two quarters, with individual characteristics fixed and the unobserved heterogeneity terms (random effects) drawn from their estimated distributions. The “unconditional” probabilities (for given characteristics, but not for given lagged labor market state) are the averages over the draws of the random effects, the conditional probabilities – given characteristics as well as the lagged labor market state – are computed as the ratio of two unconditional probabilities.⁷ Specifically, for each of the two panels, and for men and women, the average probabilities (over the random effects) of all the labor market states in the first and the second quarter are calculated for two persons, who only differ in education level. Moreover, the same characteristics are imposed for the individuals in both panels. For example, Table 5 refers to two individuals, who are both married with one young child, received higher education, are 40 years old in the first quarter of each panel, etc.. Standard errors of the probabilities are estimated by repeating the simulations for a large number of draws (1000 draws in our case) from the estimated asymptotic distribution of the parameter estimates. The results are summarized in Tables 5-8.

Several things are worth to be pointed out. First, higher educated individuals (both men and women) not only have a larger chance to be employed, but also are much more likely to be formal sector workers than lower educated persons. For example, the probabilities for the highly educated male to be a formal sector worker are 0.77 or more, versus 0.57 or less for the lower educated male. This can be seen as evidence that highly educated men are more likely to find formal sector jobs.

Second, for men of both education levels, the probability to enter the formal sector is larger for the non-employed than for informal sector workers. This is in line with the notion that it is easier to search for a formal sector job from non-employment than from informal sector employment, which is one of the assumptions underlying the staging hypothesis. On the other hand, it could also mean that some informal sector workers are not looking for a formal sector job.

Third, a salient difference between the transition patterns for men in the two panels, is that the transition rates from formal and informal sector into non-employment are larger for the second than for the first panel. This is the case for men with low as well as high education. This result could reflect higher lay-off rates during the recession, combined with the fact that some of those who are laid off do not immediately find different employment in either sector.

Fourth, the transition rates from non-employment into the formal sector are larger than those into the informal sector for the higher educated men, but given the large estimated standard errors, they are not significantly different for either panel. However, for lower educated men the transition rates from non-employment into the formal sector are smaller than those into the informal sector, and in the second panel, this difference

⁷This implies that the conditional probability is the weighted average of the conditional probabilities for given value of α_i , where the weights are posterior weights given the lagged labor market state.

is even significant despite the imprecise estimates. Given the relative sizes of the two sectors in both markets for the higher educated (0.779:0.196 in the first panel) and lower educated men (0.573:0.402 in the first panel), the estimates suggest that it is more likely to find jobs in the informal sector than in the formal sector for both higher educated and lower educated non-workers. This is concordant with the assumption that the entry of the formal sector is more restricted. Moreover, the transition rate from non-employment into the informal sector increases during the second panel, though this result is not significant. While the estimated transition rate from non-employment into the formal sector hardly changes for men with high education levels, it falls substantially for the low educated. The reason could be that during the recession, excess labor supply allows firms to hire mainly skilled workers. Again, however, this result is insignificant, due to the small numbers of non-employed men.

For highly educated females, the estimates show the same pattern as for highly educated males, although the standard errors are much larger, due to the small number of observations in this category. Few women with high education level work in the informal sector. The probability to stop working for informal sector workers is quite high. There are no larger differences between the two time periods. For low educated women, the probabilities of formal and informal sector work are almost the same. Given this and the fact that the probabilities of remaining in the formal sector (for example, 0.766 in the first panel) are larger than those of remaining in the informal sector (for example, 0.541 in the first panel), we conclude that formal sector work is more stable than informal sector work. For the higher educated females, the transition rates into the formal sector from non-employment are the same as the corresponding rates into the informal sector,⁸ but for the lower educated females, they are significantly smaller than those into the informal sector. Surprisingly, the probabilities to stay in the same sector are larger during the recession than during the upswing of the business cycle. In particular, transition rates into non-employment are lower during the recession. This might reflect the fact that fewer people could afford to be without work.

In the appendix (Table A7 and A8), we also present some results for the model with interactions (men, first panel). These simulation results are very imprecise due to both a larger number of parameters involved and the small number of observations in some categories because of the inclusion of interaction terms. Still, the picture is more or less unchanged compared to the model without interactions, and the conclusions remain valid.

⁸Parallel to the analysis for men, one might draw the conclusion that it is easier to find jobs in the formal sector for higher educated females given the relative size of the two sectors. But females nonworkers consist mostly of nonparticipants, hence the self-selection effect is prominent here.

**Table 5. Simulated Transition Probabilities
(Males, higher education received)**

j_t	$Prob(j_t)$		$Prob(j_2 j_1)$		
	$t = 1$	$t = 2$	Formal	Informal	Not-employed
92.1					
Formal	0.779 (0.035)	0.782 (0.026)	0.926 (0.019)	0.062 (0.017)	0.012 (0.005)
Informal	0.196 (0.031)	0.201 (0.024)	0.202 (0.046)	0.765 (0.050)	0.033 (0.015)
Not-employed	0.025 (0.020)	0.018 (0.011)	0.378 (0.090)	0.272 (0.109)	0.351 (0.139)
94.4					
Formal	0.797 (0.029)	0.772 (0.022)	0.926 (0.017)	0.059 (0.012)	0.026 (0.008)
Informal	0.184 (0.030)	0.195 (0.020)	0.188 (0.042)	0.771 (0.047)	0.042 (0.012)
Not-employed	0.018 (0.013)	0.033 (0.010)	0.392 (0.085)	0.336 (0.068)	0.272 (0.065)

Standard errors in parentheses.

**Table 6. Simulated Transition Probabilities
(Males, lower education received)**

j_t	$Prob(j_t)$		$Prob(j_2 j_1)$		
	$t = 1$	$t = 2$	Formal	Informal	Not-employed
92.1					
Formal	0.573 (0.040)	0.537 (0.035)	0.841 (0.032)	0.135 (0.028)	0.024 (0.009)
Informal	0.402 (0.037)	0.429 (0.030)	0.119 (0.028)	0.849 (0.033)	0.032 (0.016)
Not-employed	0.025 (0.033)	0.035 (0.024)	0.276 (0.078)	0.380 (0.124)	0.344 (0.158)
94.4					
Formal	0.537 (0.031)	0.491 (0.034)	0.807 (0.031)	0.123 (0.020)	0.070 (0.017)
Informal	0.433 (0.029)	0.434 (0.027)	0.117 (0.025)	0.822 (0.030)	0.061 (0.013)
Not-employed	0.030 (0.017)	0.075 (0.016)	0.228 (0.085)	0.408 (0.068)	0.364 (0.086)

Standard errors in parentheses.

**Table 7. Simulated Transition Probabilities
(Females, higher education received)**

j_t	$Prob(j_t)$		$Prob(j_2 j_1)$		
	$t = 1$	$t = 2$	Formal	Informal	Not-employed
92.1					
Formal	0.517 (0.082)	0.453 (0.062)	0.808 (0.064)	0.026 (0.018)	0.167 (0.056)
Informal	0.075 (0.057)	0.078 (0.033)	0.110 (0.062)	0.581 (0.120)	0.310 (0.098)
Not-employed	0.409 (0.075)	0.468 (0.060)	0.067 (0.035)	0.053 (0.029)	0.879 (0.047)
94.4					
Formal	0.487 (0.071)	0.448 (0.068)	0.851 (0.066)	0.028 (0.013)	0.121 (0.059)
Informal	0.064 (0.035)	0.076 (0.028)	0.102 (0.046)	0.616 (0.090)	0.282 (0.091)
Not-employed	0.449 (0.069)	0.476 (0.070)	0.059 (0.035)	0.051 (0.020)	0.889 (0.043)

Standard errors in parentheses.

**Table 8. Simulated Transition Probabilities
(Females, lower education received)**

j_t	$Prob(j_t)$		$Prob(j_2 j_1)$		
	$t = 1$	$t = 2$	Formal	Informal	Not-employed
92.1					
Formal	0.133 (0.035)	0.117 (0.020)	0.766 (0.086)	0.060 (0.027)	0.174 (0.070)
Informal	0.156 (0.041)	0.137 (0.029)	0.027 (0.024)	0.541 (0.065)	0.433 (0.064)
Not-employed	0.711 (0.048)	0.745 (0.031)	0.016 (0.012)	0.063 (0.017)	0.921 (0.021)
94.4					
Formal	0.145 (0.027)	0.139 (0.026)	0.843 (0.074)	0.055 (0.025)	0.102 (0.052)
Informal	0.150 (0.036)	0.139 (0.026)	0.036 (0.022)	0.600 (0.056)	0.364 (0.058)
Not-employed	0.704 (0.045)	0.722 (0.041)	0.016 (0.011)	0.059 (0.013)	0.926 (0.018)

Standard errors in parentheses.

5 Conclusions

We have investigated the function of the informal sector in urban Mexico by studying the transition patterns among the three labor market states formal sector employment, informal sector employment, and non-employment. Mobility among these three states is extremely large compared to other OECD countries. A random effects dynamic multinomial logit model was estimated using simulated maximum likelihood methods for two Mexican panel data sets covering non-overlapping time periods. Our findings are in line with the literature. The probability of formal sector employment strongly increases with education level. The probability of working in the informal sector decreases with the level of income of other family members, while the probability of not working increases with this.

The simulated probabilities of transitions for individuals in different market conditions and for different individuals in the same period were compared. We found that for lower educated nonworkers, the transition rates into the formal sector are lower than the transition rates into the informal sector. This may be an indication that the barrier of the formal sector is higher than the barrier of the informal sector. We also found, for all but lower educated men, that the probabilities of remaining in the formal sector are larger than the probabilities of remaining in the informal sector, and that the transition probabilities from the informal sector to the formal sector are larger than those from the formal to the informal sector. For lower educated women, this suggests that formal sector jobs are more stable than the informal sector, since the sizes of the two sectors are similar for this group. For the other groups, the difference might be due to the mere fact that the formal sector is larger than the informal sector, so that people who separate from their job have a higher probability of finding a job in the same sector if they are in the formal sector. Since we do not have information on job mobility, we cannot analyze the stability of jobs in the two sectors directly. Together with the descriptive statistics on wage rates, these findings suggest that for the higher educated, formal sector employment has the characteristics of primary jobs, which are superior to jobs in the informal sector. Informal sector jobs are held by those with low other family income, who cannot afford not to work at all. This is in line with the staging hypothesis in the Fields (1975) model. For men and women with low education levels, however, we find a very different pattern, and there is no evidence that formal sector jobs are superior to informal sector jobs. Thus for the low educated, the weakly competitive view of Magnac (1991) seems more relevant.

Some limitation of our approach and directions for future research seem worth mentioning. The first is that our models are reduced form in the sense that wage rates are not explicitly incorporated. An extension of the current model to a more structural model in which potential wages in both sectors are modeled simultaneously with labor market state, could be used to investigate the role of the wage differential between formal and informal sector. The differences with education level which we find with the current model, could very well reflect the impact of the wage differential in a more struc-

tural model. A second limitation is the issue of migration. Temporary migration to the U.S. is very common. See Martin (1999) for an extensive descriptive analysis. Whether the quality of informal and formal sector employment affects this type of migration, is obviously of great policy relevance for the U.S. as well as Mexico. Unfortunately however, we cannot use our panel data to take migration into account, since information on temporary migrants is not available.

References

- Calderón-Madrid, A. (1999), "Job Stability and Labor Mobility in Mexico During the 1990s'," working paper, Centro de Estudios Económicos, Mexico.
- Fields, G. (1975), "Rural-Urban Migration, urban Unemployment and Underemployment, and job search activity in LDCs'," *Journal of Development Economics* 2, 165-187.
- Fleck, S. & C. Sorrentino (1994), "Employment and Unemployment in Mexico's labor force," *Monthly Labor Review* 117(11), 3-31.
- Gourieroux, C. & Monfort, A., (1993) "Simulation based inference: A Survey with Special Reference to Panel Data," *Journal of Econometrics* 59(1-2), 5-34.
- Heckman, J. (1981a), "Statistical Models for Discrete Panel Data," in *Structural Analysis of Discrete Data with Econometric Applications*, ed by Manski, C. and D. McFadden, the MIT Press, London, 114-179.
- Heckman, J. (1981b), "The incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process," in *Structural Analysis of Discrete Data with Econometric Applications*, ed by Manski, C. and D. McFadden, the MIT Press, London, 114-179.
- Heckman, J. and G. Sedlacek (1985), "Heterogeneity, aggregation and market wage functions: an empirical model of self-selection in the labor market," *Journal of Political Economy* 93, 1077-1125.
- International Labor Office (1972), *Employment, Incomes and Equality: A Strategy for Increasing Productive Employment in Kenya*, Geneva.
- Hollon, C. (1996), "Individual Employee Employment Security under Mexican Federal Labor Law," *Labor Law Journal*, October, 648-655.
- Kopinak, K. (1995), "Gender as a Vehicle for the Subordination of Women Maquiladora Workers in Mexico," *Latin American Perspectives* 22(1), 30-48
- Lee, L.-F. (1992), "On efficiency of methods of simulated moments and maximum simulated likelihood estimation of discrete response models," *Econometric Theory* 8, 518-552.
- Magnac, Th. (1991), "Segmented or Competitive Labor Markets," *Econometrica* 59, 165-187.
- OECD Economic Surveys -Mexico, 1992, OECD publications, Paris.
- Martin, P. (1999), "Trade and Migration: The Mexican-US Experience," mimeo, University of California, Davis.
- Pradhan, M. & A. van Soest (1995), "Formal and informal sector employment in Urban Areas of Bolivia," *Labor Economics* 2, 275-297.
- Pradhan, M. and A. van Soest (1997), "Household labor supply in Urban

- Areas of Bolivia,” *Review of Economics and Statistics* 79,300-310.
- Strassmann, W. (1987), “Home-based Enterprises in cities in developing countries,” *Economic Development and Cultural Change* 36, 121-144.
- Thomas, J. (1992), “Informal Economic Activity,” in *LSE Handbook in Economics*, Harvester Wheatsheaf, Hertfordshire.
- Villagomez, E (1996), “Informal Markets: A Model of Household Labor Supply,” working paper, Universidad de Alcala de Henares.
- Villagomez, E (1998), “Mobility between the formal and informal sector: A panel data analysis for five Mexican cities,” working paper, .
- Zeleg, M., & O. de la Vega (1992), “An outline of Mexican Labor law,” *Labor Law Journal*, July, 466-470.

Appendix:

Table A1. Variable explanations

Variables	Explanation
<i>Child</i>	Number of children younger than 6 years old
<i>Adults</i>	Number of family members older than 11 years old
<i>Age</i>	Age of the individual
<i>Lowedu</i>	No education or primary school education(0-6 years)
<i>Medu</i>	After primary but up to senior school education (7-12 years)
<i>Hedu</i>	Univ. or vocational education after Senior school (12+ years)
<i>Othinc</i>	Real incomes from other family members (in pesos of July, 1995)
<i>JuaTij</i>	Ciudad Juarez and Tijuana
<i>Guada</i>	Guadalajara
<i>Mont.</i>	Monterrey
<i>Mex. City</i>	Mexico City
<i>Married</i>	Married persons
<i>Nmar</i>	Single or divorced
<i>T1</i>	Time dummy: 1 if the first quarter
<i>T2</i>	Time dummy: 1 if the second quarter
<i>T3</i>	Time dummy: 1 if the third quarter
<i>T4</i>	Time dummy: 1 if the fourth quarter
<i>T5</i>	Time dummy: 1 if the fifth quarter
<i>Form.</i>	formal sector workers
<i>Infor.</i>	Informal sector workers
<i>Noem.</i>	being not employed

Table A2. Sample Statistics

<i>Variables</i>	1 st quarter of 92		4 th quarter of 94	
	Men	Women	Men	Women
<i>Child</i>	0.720(0.87)	0.660(0.85)	1.716(0.84)	1.711(0.84)
<i>Adults</i>	3.347(1.74)	3.287(1.76)	4.166(1.53)	4.104(1.60)
<i>Age</i>	39.740(11.42)	38.670(12.13)	38.843(10.90)	37.503(11.72)
<i>Lowedu</i>	0.455(0.50)	0.554(0.50)	0.444(0.50)	0.530(0.50)
<i>Medu</i>	0.363(0.48)	0.375(0.48)	0.380(0.49)	0.391(0.49)
<i>Hedu</i>	0.182(0.39)	0.071(0.26)	0.176(0.38)	0.079(0.27)
<i>Othinc</i>	980.2(1657)	2373.1(2501)	1044.6(1719)	2524.2(3110)
<i>JuaTij</i>	0.298(0.35)	0.331(0.37)	0.277(0.35)	0.321(0.37)
<i>Guada</i>	0.178(0.38)	0.147(0.35)	0.136(0.34)	0.084(0.28)
<i>Mont.</i>	0.205(0.40)	0.211(0.41)	0.240(0.43)	0.261(0.44)
<i>Mex. City</i>	0.318(0.47)	0.311(0.46)	0.347(0.48)	0.334(0.47)
<i>Married</i>	0.940(0.24)	0.830(0.38)	0.943(0.23)	0.817(0.39)

Standard deviations in parentheses.

Table A3. Estimates of the static logit equation

Param.	the 1992 Panel				the 1995 Panel			
	Men		Women		Men		Women	
	Info.	Noem.	Infor.	Noem.	Infor.	Noem.	Infor.	Noem.
$\pi_j :$								
<i>Const.</i>	3.031**	1.960	-2.895	8.541*	0.980	-0.923*	-2.549	5.771
<i>Age</i>	-0.223*	-0.360*	-0.105	-0.367*	-0.096	-0.267*	-0.001*	-0.216*
<i>Age2</i>	0.003*	0.006*	-0.001	0.005*	0.002	0.005*	0.002	0.004*
<i>Child</i>	0.098	-0.373	0.307	0.679*	-0.152	-0.138	0.935*	0.735*
<i>Adults</i>	0.014	-0.070	0.354*	0.271	0.112	0.139	-0.084	-0.119
<i>Medu</i>	-1.115*	-0.384	-1.621*	-1.382*	-1.768*	-0.426	-2.745*	-1.805*
<i>Hedu</i>	-3.491*	-2.745*	-3.586*	-3.471*	-2.927*	-1.445*	-4.044*	-4.096*
<i>Othinc</i>	-0.060	0.026	-0.217*	-0.075	-0.062**	0.052	-0.058	0.012
<i>JuaTij</i>	0.084	0.244	-0.591	0.675**	-0.401	-0.137	-1.082**	-0.767*
<i>Guada</i>	0.485	0.273	0.985	0.526	1.053*	1.516*	-0.599	-0.596
<i>Mont.</i>	-0.690**	-0.872	0.217	0.191	-0.352	-0.149	1.144*	0.660
<i>Nmar</i>	-0.822	0.375	-0.737	-4.086*	-0.060	1.485*	-0.770	-3.802*
<i>T2</i>	0.176	0.108	0.053	-0.573	0.034	0.478	-0.170	-0.449
<i>T3</i>	-0.200	-0.581	0.664	0.676	0.999	0.434	-0.848*	0.705
<i>T4</i>	0.425	-0.852	0.657	0.667	0.832*	2.252*	1.206	0.506
$\Sigma_\theta :$								
ν_2^2	15.040*		8.365*		14.021*		21.965*	
ν_3^2	6.831*		6.523*		5.212*		9.907*	
ν_{23}	6.400*		2.451		6.047*		10.655*	

- (1) * Significant at 5% level; ** significant at 10 % level.
(2) Reference group: formal sector workers.
(3) ν_j^2 : variance of θ_{ij} , $j = 2, 3$; ν_{23} : covariance of θ_{i2} and θ_{i3} .
(4) “*Lowedu*”, “*T2*”, and “*Mex. City*”, were left out as control group dummies.

Table A4 and A5 are the equivalences of Table 2 and 3 in the text, but using Magnac's definition of the informality.

Table A4. Sample percentages of the labor market status

Quarter	92.1	92.2	92.3	92.4	93.1	94.4	95.1	95.2	95.3	95.4
Males										
Formal	65.3	64.1	65.6	64.7	62.9	69.2	67.6	66.3	63.9	64.9
Informal	28.3	27.8	27.8	28.0	28.9	24.8	24.7	24.9	26.3	26.8
Nonempl.	6.4	8.2	6.6	7.3	8.1	5.9	7.7	8.8	9.8	8.4
Females										
Formal	21.7	21.0	21.3	21.8	21.7	25.8	26.2	25.9	25.3	24.5
Informal	9.5	9.1	8.6	9.2	8.7	9.8	8.3	7.5	7.9	7.9
Nonempl.	68.8	70.0	70.1	69.0	69.6	64.4	65.5	66.6	66.7	67.6

Table A5. Sample probabilities of transitions

$t - 1$	$t = 2$			$t = 3$			$t = 4$			$t = 5$		
	Form.	Infor.	Noem.	Form.	Infor.	Noem.	Form.	Infor.	Noem.	Form.	Infor.	Noem.
<u>Men 92</u>												
Form.	0.855	0.103	0.042	0.865	0.111	0.024	0.861	0.108	0.032	0.859	0.113	0.029
Infor.	0.235	0.707	0.058	0.281	0.662	0.057	0.254	0.678	0.068	0.198	0.723	0.079
Noem.	0.186	0.186	0.629	0.225	0.225	0.550	0.253	0.187	0.560	0.211	0.155	0.634
<u>Men 95</u>												
Form.	0.847	0.118	0.035	0.845	0.100	0.055	0.842	0.104	0.054	0.868	0.090	0.042
Infor.	0.295	0.622	0.083	0.263	0.655	0.082	0.250	0.675	0.075	0.264	0.678	0.057
Noem.	0.203	0.261	0.536	0.250	0.298	0.452	0.237	0.268	0.495	0.243	0.315	0.441
<u>Women 92</u>												
Form.	0.750	0.048	0.202	0.814	0.045	0.141	0.772	0.071	0.156	0.806	0.053	0.141
Infor.	0.099	0.527	0.374	0.073	0.510	0.417	0.176	0.527	0.297	0.132	0.505	0.363
Noem.	0.035	0.050	0.915	0.042	0.047	0.911	0.049	0.044	0.908	0.045	0.039	0.915
<u>Women 95</u>												
Form.	0.822	0.059	0.119	0.837	0.038	0.125	0.827	0.035	0.137	0.814	0.053	0.133
Infor.	0.165	0.485	0.350	0.097	0.570	0.333	0.123	0.494	0.383	0.123	0.543	0.333
Noem.	0.040	0.031	0.929	0.049	0.029	0.922	0.041	0.050	0.909	0.044	0.036	0.920

**Table A6. Estimates of the unrestricted model
(Men, 1992 panel)**

Param.	Dynamic equation		Static equation	
	Info.	Noem.	Infor.	Noem.
$\beta_j :$				
<i>Const.</i>	-1.304	-2.037	2.659	2.229
<i>Age</i>	-0.012	-0.160*	-0.215*	-0.385*
<i>Age2</i>	0.001	0.003*	0.003*	0.006*
<i>Child</i>	0.194	-0.158	0.144	-0.229
<i>Adults</i>	-0.154*	-0.002	-0.037	-0.030
<i>Medu</i>	-0.980*	-0.251	-1.126	-0.374
<i>Hedu</i>	-2.993*	-1.613*	-3.428*	-3.262*
<i>Othinc</i>	-0.032	0.028	-0.052	-0.002
<i>JuaTij</i>	0.837*	0.845*	0.033	0.282
<i>Guada</i>	0.754*	0.927**	0.696	0.506
<i>Mont.</i>	-0.162	0.499	-0.811**	-0.803
<i>Nmar</i>	-0.118	1.478*	-0.758	0.276
<i>T3</i>	-0.140	-0.387	0.228	0.049
<i>T4</i>	-0.250	-0.263	-0.459	-0.927
<i>T5</i>	-0.139	-0.111	0.491	-0.634
$\gamma_j :$				
<i>Infor.</i> ₁	-1.945*	2.133*		
<i>Infor.*JuaTij</i>	-1.833*	-1.472*		
<i>Infor.*Guada</i>	-1.247*	-1.499*		
<i>Infor.*Mont.</i>	-0.070	-0.884		
<i>Noem.</i> ₁	1.436*	2.589		
<i>Noem.*JuaTij</i>	-1.430**	-1.069		
<i>Noem.*Guada</i>	-0.508	-0.169		
<i>Noem.*Mont.</i>	-0.818	-0.386		
$\Sigma_\alpha :$				
σ_2^2		10.985*		17.683*
σ_3^2		4.597*		10.679*
σ_{23}		5.378*		10.793*

(1) * Significant at 5% level; ** significant at 10 % level.

(2) Reference group: formal sector workers.

(3) $\sigma_j^2 = Var(\alpha_{ij})$, $j = 2, 3$; $\sigma_{23} = Cov(\alpha_{i2}, \alpha_{i3})$.

(4) “*Lowedu*”, “*T2*”, “*Mex. City*”, and “*Form.*”, were left out as control group dummies.

**Table A7. Simulated Transition Probabilities
(Males, higher education received)**

j_t	$Prob(j_t)$		$Prob(J_2 j_1)$		
	$t = 1$	$t = 2$	Formal	Informal	Not-employed
92.1					
Formal	0.797 (0.060)	0.783 (0.047)	0.944 (0.042)	0.047 (0.032)	0.009 (0.028)
Informal	0.198 (0.057)	0.200 (0.051)	0.145 (0.111)	0.814 (0.172)	0.041 (0.114)
Not-employed	0.005 (0.039)	0.017 (0.041)	0.336 (0.182)	0.322 (0.182)	0.342 (0.227)

Standard errors in parentheses.

**Table A8 Simulated Transition Probabilities
(Males, Lower education received)**

j_t	$Prob(j_t)$		$Prob(J_2 j_1)$		
	$t = 1$	$t = 2$	Formal	Informal	Not-employed
92.1					
Formal	0.567 (0.044)	0.534 (0.038)	0.873 (0.053)	0.109 (0.037)	0.018 (0.038)
Informal	0.409 (0.045)	0.432 (0.043)	0.082 (0.040)	0.881 (0.095)	0.037 (0.078)
Not-employed	0.024 (0.043)	0.034 (0.050)	0.232 (0.146)	0.426 (0.172)	0.343 (0.209)

Standard errors in parentheses.

Figure 1. Comparison of the real log wages between the formal sector and the informal sector (Males)

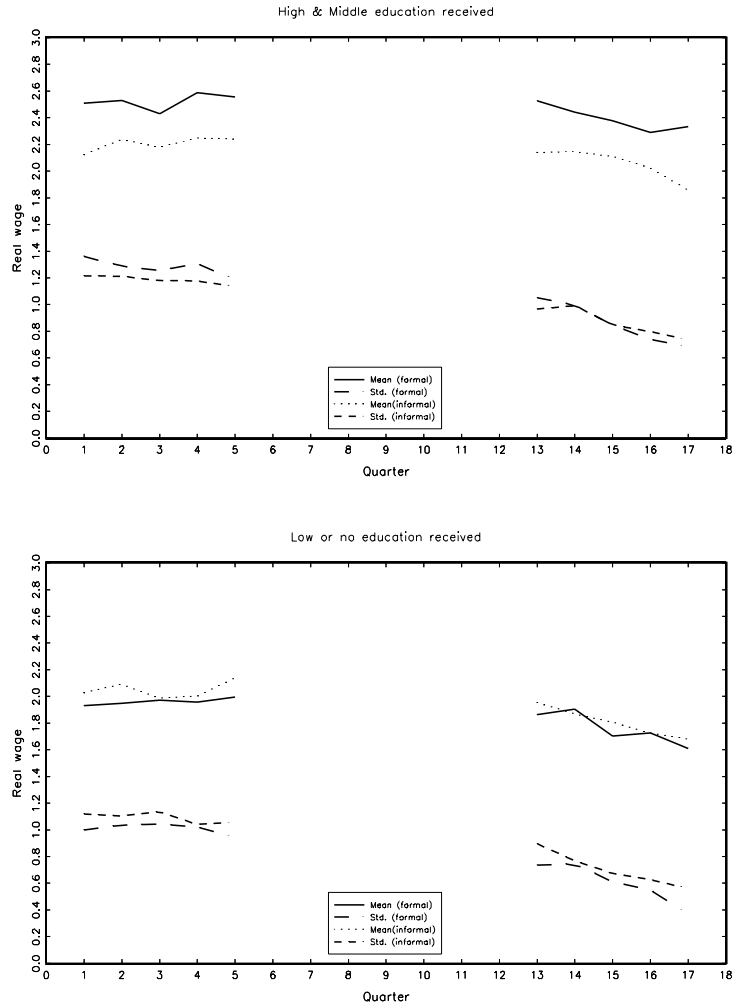


Figure 2. Comparison of the real log wages between the formal sector and the informal sector (Females)

