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Comparative Analysis of Labor Market Dynamics Using Markov Processes:

An Application to Informality

Mariano Bosch
William Maloney

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Abstract

This paper discusses a set of statistics for examining and comparing labor market dynamics based on the estimation of continuous time Markov transition processes. It then uses these to establish stylized facts about dynamic patterns of movement using panel data from Argentina, Brazil and Mexico. The estimates suggest broad commonalities among the three countries, and establish numerous common patterns of worker mobility among sectors of work and inactivity. As such, we offer some of the first comparative work on labor dynamics. The paper then particularly focuses on the role of the informal sector, both for its intrinsic interest, and as a case study illustrating the strengths and limits of the tools. The results suggest that a substantial part of the informal sector, particularly the self-employed, corresponds to voluntary entry although informal salaried work may correspond more closely to the standard queuing view, especially for younger workers.

This paper— a product of the Chief Economist Office for Latin America and the Caribbean Region—is part of a larger effort in the department to understand the dynamics of developing country labor markets and the role of informality. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at wmaloney@worldbank.org.

Comparative Analysis of Labor Market Dynamics Using Markov Processes: An Application to Informality

Mariano Bosch
London School of Economics
m.bosch@lse.ac.edu

William Maloney
World Bank
wmaloney@worldbank.org

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I. Introduction

Traditional static analysis of labor markets provides evidence on stocks of workers found in different labor markets states, but can tell us nothing about where those workers arrived from, how long they will stay, or where they will go next. The importance of answering these questions and developing the tools to do so has been increasingly apparent in the mainstream literature, for example, on the causes of unemployment, (whether due to shedding of labor by firms or reduced hiring) or in understanding the different motivations behind being unemployed vs. out of the labor force (see, for example, Flinn and Heckman 1982, Blanchard and Diamond 1989, Shimer 2005 and Hall 2005). Increasingly, panel data sets are becoming available in the developing world that facilitate greater understanding of how those labor markets function and how they may differ from advanced country markets.

This paper discusses and develops a set of statistics based on the estimations of continuous time Markov transition processes and employs them to study and compare labor market dynamics in three developing countries Argentina, Brazil and Mexico. The methods of estimating instantaneous probabilities (intensities), durations, and probabilities conditional on separation (propensities) as well as the discussion of the embeddability of the estimated transition matrices follow closely the work of Fougère and Kamionka (1992 a,b,c). We discuss the importance for inference of conditioning on both rate of separation and job turnover in the destination sector and show that a statistic that adjusts for both has the interpretation of workers' revealed comparative advantage for particular sectors. The estimates suggest broad commonalities among the three countries, and establish numerous common patterns of worker mobility among sectors of work and inactivity. As such, the paper offers some of the first comparative work on labor dynamics.[1]

[1] See Bosch and Maloney (2005) for the first application of continuous time Markov processes to Argentina, Mexico and Brazil and more recently, in a discrete context, Duryea et. al (2006) that examine both Eastern European and Latin American data.

We focus in particular on one question with important similarities to the advanced country literature noted above- the role of the informal labor market- both because of the topic's intrinsic interest, and because it offers a case study through which to view the strengths and weaknesses of these tools. Though a notoriously elusive concept, we define the informal sector as comprising the mass of owners of and or workers in small firms who are uncovered by labor legislation.[2] At the risk of excessive stylization, one view with conceptual roots in Harris and Todaro (1970) equates the informal sector with underemployment or disguised unemployment- the disadvantaged sector of a market segmented by rigidities in the "formal" or covered sector of the economy.[3] However, another emerging view keys more off the mainstream self-employment literature in the style of Lucas (1978), Jovanovic (1982) and Evans and Leighton (1989), and argues that, as a first approximation, entry into the sector should be seen as a vocational choice in line with the worker's comparative advantage, to work in a more entrepreneurial sector, albeit one with irregular relations with the state.[4]

We show that nature of the aggregate Markov-based statistics as reduced forms capturing both comparative advantage considerations as well as barriers to mobility makes drawing inferences from the observed patterns difficult. We therefore explore additional identification strategies exploiting some of the predicted patterns of worker dynamics suggested by the competing hypotheses about informality.[5] The results suggest that a substantial part of the informal sector, particularly the self-employed, corresponds

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[2] A minority, generally no more than 25% of the informal salaried workers are found in firms of over 6 workers (see Perry et. al 2007) so this is primarily a micro firm phenomenon.

[3] This is, in fact, an extreme stylization although its essential focus on the dualism of the labor market and the intrinsic inferiority of informality is common to many models. See Schneider and Enste (2000) for a more comprehensive review of existing views. A rich theoretical literature is emerging that poses more sophisticated mechanisms that relate informality to unemployment. See, for example, Boeri and Garibaldi (2006).

[4] See for instance, Rauch (1991), Loayza (1996), Maloney (1999, 2004), Boeri and Garibaldi (2006), de Paula and Scheinkman (2007), Loayza and Rigolini (2007) postulate a continuum of entrepreneurial ability and workers sorting themselves among different formal and informal sectors of work.

[5] The two views are, of course, compatible to some degree given the heterogeneity of the sector, and existing theory can accommodate this: a turnover based efficiency wage model such as that of Stiglitz (1974) allows for firms raising wages above market clearing to deter workers from entering self-employment and, in the process, creating involuntary informality. The issue is really one of degree- what the "stylized" view of the functioning of the sector should be.

to voluntary entry although informal salaried work may correspond more closely to the standard queuing view, especially for younger workers.

II. Methodology

Estimating continuous time Markov processes

As Fougère and Kamionka (1992a) note, an earlier generation of studies focused on estimating transition probabilities between two periods of time in the context of a discrete time Markov chain.[6] More recent work, including theirs for France and Kalbfleish and Lawless (1985) seek to use discrete panel data to estimate the transition intensities from an underlying continuous Markov process. This has several advantages. First, as pointed out by Singer and Spilerman (1973), the natural time scale for many mobility processes is not a discrete sequence of intervals such as generations or decades but a continuum of time points. Labor status mobility can be viewed more realistically as a process in which states changes occur at random time points, and probabilities of moves between particular states are governed by Markov transition matrices. Secondly, as suggested by Fougère and Kamionka (2003), the analyst has access to individual panel data, which, in general, do not provide observations of continuous labor market histories, and they do not allow identifying directly measures of duration of individual employment and unemployment spells, or the probability to become unemployed at the end of an employment spell.

One way to draw statistical inference of such parameters is to assume that the observed discrete-time mobility process is generated by a continuous-time homogeneous Markov process. We assume a homogenous Markov process X_t defined over a discrete state-space $E = \{1,\ldots.K\}$ where K is the number of possible states (job sectors) a worker could be found in. The worker if observed at equally distanced points of time. With that information one can construct a discrete time transition matrix $P(t,t+n)$ where

[6] Notable examples of such estimates of labor market transitions would include Hall (1972), Toikka (1976), Clark and Summers (1979) Akerlof and Main (1981) and Poterba and Summers (1986) for the US. See Hamilton (1994) for a concise explanation of Markov chains.

$$p_{ij}(t,t+n)=\Pr(X(t+n)=j \mid X(t)=i \text{ for } t=0,1,2,..., \text{and } n=0,1,2,...,$$

The interpretation of p_{ij} is simply the probability of moving from state *i* to state *j* in one step (*n*). Discrete time matrices are easily straight forward to compute as the maximun likelihood estimator for p_{ij} is $p_{ij}=n_{ij}/n_i$, being n_{ij} the total number of transitions from state *i* to state *j* and n_i the total number of observations initially in state *i*. As $n \to 0$, this gives rise to a *k*x*k* *transition intensity* matrix *Q* where

$$\frac{dP(t)}{d(t)}=QP(t) \qquad (1)$$

whose solution is given by:

$$P(t)=e^{tQ} \qquad (2)$$

where *Q* is a *k*x*k* matrix whose entries satisfy

$$q_{ij}=\left\{\begin{array}{c} q_{ij}\in R^{+}, j\neq i, i, j=1,...,K \\ q_{ii}=-\sum_{k=2,k\neq i}^{K} q_{ij}\leq 0, j=i,=i=1,...K \end{array}\right\} \qquad (3)$$

Thus, the elements q_{ij} can be interpreted as the instantaneous rates of transition from state *i* to state *j*. In practice, the estimation of the continuous time transition matrix is subject to two major difficulties. First of all, solution to equation 2 may not be unique. This is known as the aliasing problem. That is, it is possible for an observed discrete time matrix to have been generated by more than one underlying continuous matrix. On the other hand it is possible that none of the solutions obtained for *Q* is compatible with the theoretical model expressed in equation 1 where the elements of *Q* have to satisfy a set of restrictions shown in equation 3. This is known as the embeddability problem.

Two main approaches have been followed by the literature to estimate the *Q* matrix and draw statistical inference.[7] Kalbfleisch and Lawless's (1985) maximum likelihood procedure estimates the elements of *Q* using a quasi-Newton or scoring algorithm. The main drawback of this approach stems from the fact that if *P* is not embeddable, then inference using the maximum likelihood is not reliable as standard asymptotic theory no longer applies[8].

Geweke et all (1986) propose a Bayesian procedure for statistical inference on intensity matrices as well as any function of the estimated parameters by using a uniform diffuse prior which allows to establish the probability of embeddability of the discrete-time matrix. Roughly speaking, the method consists of drawing a large number of discrete time matrices from a previously defined "importance function," assessing their embeddability and constructing confidence intervals of the parameters or functions of interest using only the posterior distribution of those matrices that turn out to be embeddable. This also provides a very natural way of assessing the probability of embeddability as the proportion of the embeddable draws. We have followed this approach, which has also been employed in Fougère and Kamionka (1992 a,b,c).

Controlling for likelihood of separation and measuring duration

The intensities simply tell us the probability of a worker moving across a sector but do not permit any inference relative desirability or ease of entry since they combine the latter with any intrinsic disposition to separate. Hence, a statistic standardizing on probability of separation, the *propensity*, facilitates comparing entrants into a particular terminal sector from distinct sectors of origin.

[7] For an excellent overview of this topic see Fougère and Kamionka (1992a)
[8] The reader is again referred to Fougère and Kamionka (1992a). For an earlier very preliminary paper estimating continuous time matrices for Mexico and Argentina using this technique see Arango and Maloney (2000).

We obtain this propensity decomposing the intensity matrix Q into two more manageable indicators: rate of separation and propensity to move. This can be done factorizing the intensity matrix Q as $\lambda(M-I)$ where

$$Q=\begin{pmatrix} -q_{11} & & & \\ & \cdot & & \\ & & \cdot & \\ & & & -q_{kk} \end{pmatrix}\left(\begin{bmatrix} 0 & & \\ & \cdot & r_{ij} \\ & & \cdot \\ & & & 0 \end{bmatrix}-I\right)$$

and where elements $r_{ij}=-q_{ij}/q_{ii}$ for $i \neq j$ and $i=1,...,K$. From this, we can back out average duration in state *i* which can be shown to be distributed exponentially

$$d_i \sim \exp(-q_{ii}),$$

and which, in turn, allows us to retrieve the mean duration time en each sector as

$$E(d_i)=-q_{ii}^{-1}$$

The r_{ij} elements provide a measure of transition probabilities conditional on the general rate of turnover in the sector. This can be interpreted as "if all workers were to leave their initial sector at the same rate, what would be the probability of ending in each sector." a concept we will refer to as the "propensity." The propensity matrix is especially useful when comparing rates of transition for different groups of the populations. For instance, the intensity of transition into sector *j* from sector *i* may be higher for group *h* than for group *g*, $q_{ij}^{(h)} > q_{ij}^{(g)}$, but this may only imply that more type *h* workers leave sector *i* at any instant than workers type *g*. If we seek to understand the predisposition of a moving worker to enter one sector relative to another, we need to compensate for turnover. Turnover, of course, may be somewhat determined by the choices available to move to and hence this separation must be seen as a limiting case of independence of the two. However, the point is important and has implications, for example, for standard multinomial logit analysis. Relative odds ratios of say, a particular type of workers entering a particular type of employment are often interpreted as capturing intrinsic relative preferences of that type of worker relative to others types. In fact, it may purely capture higher levels of separation of that class of worker into all types of employment.

Controlling for job openings; measuring comparative advantage

If we are only interested in movements of workers from different sectors to a common destination, then the propensity is adequate. However, comparing tendencies of transitions to multiple destinations introduces complications analogous to those the propensity measure in compensating for on the sector of origin side. A worker leaving school may be more likely to enter a given sector purely because there are more jobs available in that sector, rather than capturing any intrinsic preference for that sector. Hence, some standardization on the availability of jobs is desirable. Maloney (1999) standardized on terminal sector size, implicitly comparing observed rates of transition to what would occur in a random reshuffling of all workers across sectors. However, standardizing on terminal sector size implicitly assumes that positions in all sectors open at the same rate. A better measure would account not only for size, but rate of opening, thereby comparing observed transitions with a random allocation across available positions in all possible destination sectors, Tij=rij/() where () is a measure of new openings in sector j as a proportion of total new job created in the economy available for the individual in sector.

In fact, Pages and Stampini (2006) propose a T matrix that does this :

$$T_{ij} = \frac{r_{ij}}{\dfrac{n_{\cdot j} - n_{jj}}{\sum_{k \neq i} n_{\cdot k} - n_{kk}}}$$

where r_{ij} is the propensity (probability of transiting given separation) of going from sector *i* to sector j , $n_{\cdot j}$ is number of individual moving to sector *j* from any other sector and n_{jj} is the number of individuals who started in sector *j* and remained in sector *j*. The authors interpret $n_{\cdot j} - n_{jj}$ as the total number of jobs created in sector *j*, although it literally captures the total number of new entrants in sector j which includes rotation in existing jobs as well. Similarly, $\sum_{k \neq i} n_{\cdot k} - n_{kk}$ captures loosely speaking the total number of jobs openings available for individuals that leave sector *i*. Hence T_{ij} can be interpreted as the propensity of transiting from *i* to *j* controlling for job openings in sector *j* as a proportion of total openings available for individuals existing sector *i*. It is straightforward to show that rates of separation from sectors of origin net out so that in continuous time this is, in fact, the R matrix of propensities standardized by job openings.

Importantly, we call attention to the fact that the T matrix's structure can be seen as the ratio of i's probability of transiting into j over its probability of transiting into any sector not equal to i, relative to the analogous ratio for the entire workforce. It thus takes the same form as the Balassa (1965) measure of Revealed Comparative Advantage in trade where the measure is a country's relative exports of good relative to the global analogue. Thus, the T matrix, assuming the absence of any barriers to mobility, can be seen as a measure of revealed comparative advantage in the labor market. The idea that workers' relative endowments of characteristics determines their comparative advantage in different types of jobs appears in Lucas' (1978) discussion of choices between salaried work and self-employment, and explicitly in Rosen (1978), Heckman and Sedlacek (1985), Carneiro, Heckman and Vytlacil (2005). That we normally think of workers as completely specializing (although in fact many may hold two or more jobs) is analogous to the case where international prices lead countries to dedicate all of their resources to the production of one good. As in standard limited dependent variable analyses, when we aggregate across many individuals, unobserved characteristics may cause observationally equivalent workers to be stochastically allocated across several sectors rather than being uniquely found in one.

Thinking of T as measuring comparative advantage offers some intuition for the patterns of movements we identify across sectors. The more two sectors are similar in the worker characteristics used "intensively," the more we may find them showing very similar patterns of revealed comparative advantage. In the limit, and with no barriers to entry or mobility, we might expect T values characterizing flows between those sectors to be of similar magnitudes in each direction. Again following Lucas, we might find that workers with a comparative advantage in salaried work may show higher T's among salaried positions in both the formal and informal sectors than relative to self-employment.

Mobility

Finally, as in Bosch and Maloney (2005) we employ an overall measure of mobility of the intensity matrix to assess the can be computed following Geweke, Marshall and Zarkin (1986) who extend the work of Shorrocks (1978) in the construction of mobility indices in discrete time to continuous time models. This index satisfies a series of desirable properties such as monotonicity, strong immobility; velocity and freedom from aliasing (see Geweke 1986). It takes the form of

$$M(Q) = -tr(Q)/K$$

Since aggregate mobility is thought of as a benchmark of labor market flexibility (see for example Nickell 1997), this measure is of potential interest.

Identification issues

An important caveat accompanies all these measures: they are fundamentally reduced forms combining elements of comparative advantage (worker endowments and preferences) and demand factors which are affected, as in the traditional market segmentation hypothesis, by any barriers to the free allocation of labor across sectors. Hence, while a finding of a high degree of symmetry of T statistics, for instance, is suggestive of unrestricted allocation, it is also potentially consistent with other scenarios where there are barriers to movement. Hence, additional sources of identification are important to provide insight into the factors driving a particular transition. We explore two types. First, we look at the variance across worker characteristics and in particular across age, education, and gender. Second, taking Mexico as an example, we look at the pattern of mobility across time and how they vary across the business cycle. In both cases, existing theory provides potentially identifying restrictions.

III. Data

To construct the time continuous matrices we employ three different surveys which compile information about labor status of workers and other relevant information.

Mexico

The Encuesta Nacional de Empleo Urbano (ENEU National Urban Employment Survey) conducts extensive quarterly household interviews in the 16 major metropolitan areas. The questionnaire is extensive in its coverage of participation in the labor market, wages, hours worked, etc. that are traditionally found in such employment surveys. The ENEU is structured so as to track a fifth of each sample across a five quarter period. We have concatenated panels from the first quarter of 1987 to the forth quarter of 1999. For each individual contributed with tow transition pairs (from 1st quarter to the forth and second to the fifth.) giving rise to approximately 1,785.000 transitions, 810,000 for men and 975,000 for women.

Argentina

In a similar fashion for Argentina, we use the Encuesta Permanente de Hogares (EPH Permanent Household Survey), a panel covering the area of the Federal District and surroundings (Gran Buenos Aires), which accounts for approximately 60% of total Argentina employment. The survey is conducted every 6 months (April/May and October) with a 25% rotation of the panel. As a consequence, each household is followed for two years at sampling intervals of six months. We employ panels from May 1993 to October 2001. The sample is notably smaller than the Mexican and Brazilian surveys and we can only study 29,000 transitions, 13,900 for men and 15,100 for women.

Brazil

The Pesquisa Mensual do Emprego (PME- Monthly Employment Survey) follows monthly employment indicators. Households are interviewed four months in a row, and then re-interviewed eight months later. 25% of the sample is renewed every month. Given this panel structure we can construct four yearly employment status transitions for each individual. We have put together 9 consecutive panels starting in February 1982. Each panel consists of 12 consecutive cohorts covering approximately 2 years covering the period 1982-2001. The total number of transitions is 2,520,000: 1,190,000 for men and 1,330,000 for women.

Sectoral definitions

We divide the labor force into three sectors of work: formal salaried, informal salaried and self-employed. While the term "informal" suffers from overly broad and imprecise usage, it refers here to owners (self-employed) and workers (informal salaried) who do not have social security or medical benefits and are therefore not protected. Formal salaried workers are defined as those enjoying labor protections. The remainder of the sample is divided into two groups those out of the labor force, and the unemployed.

The sample was further divided into two education groups, those with 8 or less years of education (low education) and those with more than 8 years (high education) as well as three age groups: less than 24 years of age, 24 to 40, and then above 40. We follow Kamionka and Fougere in assuming time homogeneity within each age class but not necessarily across age classes. That is, we hypothesis that if t is the calendar time, and a the age of the individual, $q_{ii}\ (t,a) = q_{ij}(a) = q_{ij,m}$ where *m* corresponds to each of our sub-divisions of the sample. Table 1 retrieves the summary of the population distribution among different sectors split according to age and education.

IV. Patterns of Mobility

We estimate continuous time matrices from the discrete transition data as described above. Table 2 reports the posterior probability of embeddability and suggests that the Brazilian and Mexican matrices are clearly embeddable for all different subgroups. Argentina, however, shows probabilities near unity for the overall matrix and runs into problems when the division of the sample reduces the number of observations.

Tables 3a-c present the estimated Q matrices of intensities-the instantaneous probability of moving from sector i to j, and its two component parts, the rate of separation from the each sector, transformed into the mean duration of stay in the sector, and the matrix of propensities to move from i to j conditional on separation from the previous state.[9] The intensities, propensities, and the propensities adjusted by job openings (the T matrix) for select sectors of interest are shown in figure 1a and b, and the durations in figure 2. The Q matrices suggest that the three labor markets are broadly of the same phylum, showing a high degree of commonality in most any arbitrarily chosen transition. Argentina does differ in some key aspects that seem especially related to the very high rates of unemployment as we discuss below. Hence, were we to study the markets at the same point in the business cycle, even greater commonalities may emerge.

Transitions between formal and informal jobs.

Analysis of the transitions among sectors of work provides the clearest illustration of the relative merits of the different statistics developed above. It is also in the realm of intersectoral transitions that some of the strongest hypotheses about the functioning of the developing country labor market have been postulated.[10] Again, more traditional segmentation models would predict than, on average across the business cycle, workers

[9] In the interest of space, we do not report the complete T matrices as well. Available on request.
[10] Ideally, we would have data that permit studying job to job movement including those within a sector - which evidence from the US suggests is vast (Nagypal 2004), but we do not. However, for the purposes of identifying patterns of interaction among the informal and formal sectors, this is not a major drawback.

may graduate from informal jobs into formal jobs, much as third graders graduate into fourth grade. However, if informality is just one of many characteristics of jobs of overall equal quality attracting workers with similar comparative advantage, then we might expect conditional flows in both directions and, as discussed before, of comparable magnitudes.

Figures 1a and b provide graphical representation of the three sets of transition matrices corresponding to the raw intensities, propensities, and propensities adjusted for job openings (the T or comparative advantage matrix). What is immediately obvious from the intensities is that there is a high degree of similarity in flows across countries and across sectoral pairs. In all countries, formal salaried-self-employment flows are small relative to informal salaried-self-employment flows and, especially, informal salaried-formal salaried flows. In particular Brazil and Mexico, the magnitude of the flows is quite large. Most dramatically, between 40 and 50% of informal salaried workers will transit to formal sector jobs across the course of a year. These labor markets appear very dynamic. Also striking is the large asymmetry in the informal salaried/formal salaried flows that do, indeed suggest a more traditional queuing view of the sector. The probability of moving from informal salaried to formal salaried is much higher than in the reverse direction.

However, moving from intensities to propensities the flows are more symmetrical and, in some cases reversed. For Argentina and Brazil, the relative flows among the four sectors are reversed moving from intensities to propensities except for one case, and in Mexico the formal-self-employed and formal-informal flows become far more symmetrical. Again, this illustrates a more general issue: logit exercises that seek to explain entry into self-employment from informal salaried and formal salaried sector will suggest “easier” entry from informal salaried when, in fact, there may just be more separation.

Turnover, duration and labor market flexibility

What is driving the substantial change in our picture of relative mobility, by construction, is the adjustment for rates of turnover in the initial sector. As a means of illustrating the importance of this, Figure 2 plots the absolute mean duration of stay, the inverse of turnover, in each sector. Again, the similarities across countries are far more striking than the differences. In all three countries, for both men and women, formal employment shows the longest average duration, around 4.5 years. Informal forms of employment show lower duration/faster turnover. This is particularly the case for informal salaried work which consistently across countries shows an average duration of around a year. Hence, it is not surprising that standardizing on these very different rates of turnover changes the observed inter-sectoral mobility intensities so much.

There are important differences that are worth noting. Argentina shows a much higher duration in unemployment than the other two countries and, in contrast to the other two countries which show constant duration across ages, a rise among younger and older entrants (figure 3a). Both plausibly, reflects the very depressed labor market across the sample period. Although the ranking of duration- formal employment, self-employment and informal salaried employment- is shared by women as well, they also show far longer spells out of the labor force, and substantially shorter duration in self-employment activities compare to their male counterparts. We will explore the logic behind this in the next section. In both self-employment and formal salaried work, although not in informal salaried, duration is higher among older and more educated workers.

Table 4 presents the Geweke, Marshall and Zarkin (1986) mobility index for the three countries, by country, gender age and educational group. Argentina emerges as the country with the least mobility for all groups with Mexico and Brazil more or less similar to each other, with Mexico only slightly more mobile in most of the subgroups. The Argentine matrix appears “slower” even controlling for the higher level of education and age of the country.

Adjusting for job openings and measuring comparative advantage

The third panels of Figures 1a and b, present the adjusted propensities (T matrix) and suggest several stylized facts. First, again particularly among the men, the patterns are remarkably similar across countries. Second, the relative symmetry of the majority of pairs of flows when controlling for turnover and job creation, is striking, as might be the case if the calculation were being driven by comparative advantage as opposed to a more traditional one way segmentation story. This is particularly the case in Mexico for all sectors although the informal salaried-formal salaried pairing in Argentina and the self-employment-formal pairing in Brazil are also quite similar. On the other hand, the larger conditional flows into formality from both informal sectors in Argentina and into formality from informal salaried in Brazil may suggest the more traditional graduation pattern found in the segmentation literature.

Finally, the T values between formal salaried and self-employment, while roughly symmetric in all cases, are lower than those found among either of the other sectors. This may suggest that, as Lucas suggested, the skills needed for each are substantially different. Salaried workers of both formal and informal sectors have similar skills.

II. Approaches to Further Identification

Several notes of caution are necessary when making such inferences. First of all, these statistics are all reduced form estimates and thus they combine disposition to enter and ability to enter. Hence, we cannot distinguish with confidence, for instance, whether the informal salaried prefer other sectors to enter self-employment, on average, or whether they may face barriers to entry-credit constraints, for example, as suggested by Evans and Jovanovic (1989). Second, an observed asymmetry of flows may reflect compositional effects of aggregating across groups with different endowments and hence different comparative advantages. As table 1 shows, for example, self-employed workers are substantially older than the salaried workers, whether formal or informal.

The next sections approach these identification issues by disaggregating the data in two ways. First, we exploit regularities that theory or empirical findings from the advanced countries offer across age, education, and gender. In particular, since informality is sometimes associated with disguised unemployment, we focus on an additional set of transitions- those in and out of the labor force. Second, we disaggregate across time, using recent findings from the US on the relationship between job finding/losing rates across the business cycle shocks for identification.

Transitions into employment by age, education and gender

The patterns of entry into different sectors of work from OLF and unemployment by age, education and gender offer information that is potentially useful for identifying among hypotheses of the forces driving or inhibiting transitions. Since we are looking at transitions into a common terminal sector, the propensities are sufficient to capture disposition. Figures 3 and 4 show the mean duration in each sector, and the propensity to enter employment by age and education, for males. Both are broadly similar for females.

The intensity matrices in tables 3a, b and c suggest that in both Mexico and Brazil, workers are more likely to move directly from OLF into employment than to pass through a period of search in unemployment. Argentina, however, appears to present a special case where almost 65% of men leaving OLF go into unemployment, a number triple the other countries for both genders, again, suggesting special difficulty in encountering work in that country.

In Mexico and Brazil, aggregate accessions from both unemployment and inactivity are not greatly out of proportion to the relative shares of job openings in the different sectors suggesting, again, that there is little obvious queuing that would lead to a disproportionate share of entry into work through that sector. However, again, in Argentina a disproportionately high 70% of all accessions occur into informal jobs suggesting substantial search to find a job and that that job tends to be informal salaried.

Figure 4 suggests that, once disaggregated by age and education more complex stories emerge that demand a nuancing of the aggregate relationships identified above. Most notably, the informal self-employed are similar to their first world colleagues in their differential behavior by age. In all three countries, the probability of entry into self-employment for young workers from OLF or unemployment is a mere fraction of that for older workers. 10% or less of young workers (16-24) leaving OLF and unemployment choose self-employment as their entry point in the labor market, around 3 times less the rate of mature workers (40-60). Thus, self-employment is not a port of entry into work. Evans and Jovanovic explain the analogous patterns in the US by arguing that, despite a presumably lower level of risk aversion among the young, they are not able to enter due to credit constraints and must wait until they have accumulated capital.

Figure 3b also suggests that older and better educated workers spend longer spells in self-employment. This would be consistent with the mainstream firm dynamics literature that suggests that, while entrepreneurship is a desirable destination, young firms, which, *ceteris paribus* are more likely to be opened by young workers, have very high failure rates (see Jovanovic 1982 and Evans and Leighton 1989). Both patterns might, alternatively, be driven by separated older workers being progressively unable to find formal sector jobs. However, the rate of transition into the sector in all three countries seems concave in age: we see a gradual increase with something of an inflection point at prime age, after which the propensity to enter begins to increase at a decreasing rate. This pattern seems more consistent with an interaction of risk aversion and the accumulation of sufficient human and physical capital than self-employment being primarily a refuge of discarded older workers. Nonetheless, this is an obvious case where the observed probability appears to be capturing both a desire to enter, and restrictions to doing so, although in this case, the barriers to entry are into the informal sector.

Gender offers additional information that suggests more comparative advantage considerations than barriers to entry into formality. For women, there is an especially dynamic corridor between self-employment and OLF: The propensity of women to move from OLF to self-employment is 2.3 (Brazil), 3.3 (Mexico) and 8 (Argentina) times higher than for males, and the reverse flows are higher than to any sector of work. In fact, the rapid transitions between these two sectors largely explain the higher mobility indexes for women than for men (See tables 3a-3c). As with older workers, this pattern may reflect especially high barriers, perhaps arising from discrimination, to women entering formal salaried work. However, in an alternative view, with lineage to Becker's (1991) work stressing structural determinants of employment patterns, Cunningham (1996) argues that Mexican women's patterns of participation and particularly their gravitation toward self-employment are driven by their need to balance their other responsibilities in the household: child raising requires a greater job flexibility than the salaried sectors offer. Overall, women do show a lower propensity than men to transit to self-employment from unemployment suggesting that this is not a sector of last resort after search.

But a stronger test should be that women without family responsibilities should show patterns closer to those of men. Table 5 extracts a cohort of single women for the two surveys with a marital status variable, Argentina and Mexico. The intensity matrices of single women are now very similar to those of men and this similarity holds up when disaggregated by duration and propensity. Further, most of the difference in OLF duration,[11] the propensities to transition into OLF from every sector, and transitions from OLF into self-employment are explained by marital status.[12] In sum, comparative advantage considerations, in this case generated by the woman's need to balance child

[11] In fact Argentine single women now spend *less* time OLF than men do. Similarly, Mexican single women spend 2.8 years in OLF instead of 3.9 for their gender overall, far closer to the mean spell of men, 2.21.

[12] In other dimensions, single women appear to have largely standard male labor market patterns. In both countries, they appear to enter from OLF into search and directly into formal salaried employment at the same rates as men and from unemployment they enter with propensities as high or higher than men.

rearing, seems to explain many of the observed transitional patterns and, in particular, the exaggerated patterns of entry into informal self-employment.

These findings contrast strongly with the patterns of entry into informal salaried work. Table 2 and Figure 4a and 4b suggest that the sector is very particular: entry is heavily weighted toward the young and, in contrast to self-employment, entry decreases with age from either unemployment or OLF. The one exception appears to be that entry in Brazil again rises for older workers from OLF, although still to levels below those of the young. This, combined with the high rates of turnover in the sector, suggests that this may be a sector of entry through which young people rapidly pass through on their way to preferred desitinations.

Transitions out of Employment

Exit flows from employment are broadly similar in all three countries. However, they offer fewer clear identification hypotheses than those offered by entry patterns. Informal salaried jobs present higher rates of job separation towards both unemployment and inactivity than other sectors of employment. Moreover, the exit rates from informal salaried jobs surpass those of their informal self-employed or formal counterparts in any age, gender and education cell. These patterns, reflected in unusually short tenure (figure 2) may reflect either the lack of attachment to the labor force of informal workers, the need to leave work to search for preferred jobs, or alternatively the higher propensity of the micro firms where most of these workers are found to destroy unprotected jobs vs protected formal jobs. The fact that the informal self-employed, those running the micro firms, by contrast, show rates of job separation that are comparable and sometimes even lower than formal sector workers and hence substantially higher tenure, again supports the interpretation that informal salaried work is not considered as desireable as the the other two sectors. The very high transition rates back into OLF for the young (figure 5a) potentially suggests movements between school and temporary work. Comparing across countries, Argentina stands alone in its disproportionate rate of job separation towards unemployment and a somehow lower rate of job separations towards inactivity, again suggesting a recessional labor market (See Blanchard and Diamond 1990).

In all three countries, a very strong tendency exists for the informal self-employed and informal salaried to transit into unemployment and, in fact, arguably, the informal contribute more to unemployment than the formal salaried. Table 6 shows a breakdown of the new unemployed by sector of origin computed using original sector sizes and the estimated intensities to calculate flows. Surprisingly a large proportion of the unemployed actually were previously employed in the informal sectors (40% in Brazil and 50% in Mexico). This is especially acute in Argentina where unemployment hovered at 20% in recent years. Overall, 60% of job destruction had its origin in the informal sector.

What this means is less clear. On the one hand, these findings are consistent with those from the industrialized countries that micro firms have very high rates of failure, and hence failed entrepreneurs and their informal salaried employees are likely to find themselves frequently unemployed. It is somewhat less consistent with the sector being a reliable safety net for separated workers who cannot afford to be unemployed and who search for new jobs from the informal sector, although, clearly the two views are compatible.

Transitions across the Business Cycle

Disaggregating temporally can provide additional identifying restrictions. For example, standard matching models in the Pissarides (2000) tradition postulate that search for new jobs- should accelerate in expansions when the probability of finding a job is higher. This is consistent with the findings from a relatively integrated market such as the US, where we find that upturns are accompanied by increased search of workers across jobs- job to job transitions are procyclical (see Nagypal 2004 and Shimer, 2005b): If formal and informal markets offer jobs of overall equivalent quality, albeit different packages of characteristics, we would expect similar patterns. On the other hand, the traditional segmentation view would argue that in periods of economic expansion, the increased availability of formal sector jobs, and the reduction in separations, should lead to increased flows from informality toward formality, and reduced flows in the opposite direction.

To keep the analysis compact, we examine only the Mexican market from 1987-2004, a period that includes two periods of recovery and crisis.[13] Figure 6 shows the evolution of the share of the work force in unemployment, as well as the share of formality over total employment sector's share of the labor market[14] The increase in informality in both periods of high unemployment suggests a very traditional view of the behavior of the role of the informal sector as a shock absorber for the formal sector and perhaps a kind of disguised unemployment.

However, again, the simple stock variables hide important information. Figure 7 shows the flows in and out of formal employment. As expected, we observe pro-cyclical transitions from informality to formality. But, contrary to the segmented view of the labor market, we find virtually identical pro-cyclical transitions from formality to informality, especially to self-employment. In fact, the HP filtered correlation between the formal-self-employment bilateral flows is 0.9. There is an unusually high transition rate from formal employment into self-employment during the 1987-91 boom that mirrors, in fact, exceeds the reverse movement from the formal sector. This suggests that there was a particularly strong re-matching between these two types of employment during that recovery. There is a decline in sector to sector search going into the crisis and then a recovery again mirrored, although more weakly, in the reverse transition. Similar

[13] In this case we take full advantage of the ENEU and compute the quarterly transitions across employment status as described in section II. We also smooth the series using a moving average smoothing with a three quarter window.

[14] The share of the formal sector remained reasonably constant from 1987 to 1991 period showing a slight decrease in the share of formality from 59% to 57% of total employment, despite a continued decrease in unemployment rate. Thereafter, it remains stable around that level up to the eve of the crisis in which it bottoms out at 53%. After the devaluation, it began a sharp recovery, regaining its earlier highs by 2001. Finally, despite the fact that the 2001 recession was substantially milder than the Tequila Crisis, formality rates fell again to around 54%. These movements are largely mirrored by the movement of unemployment from 3% in 1989 to 8% during the crisis and then again down to the lowest levels in the sample in 2001, with a slight increase in the last three years of the sample.

evidence, although with lower overall correlation, is found in the transitions between formal employment and informal salaried.

The cyclical patterns do shed some more light on the link between informality and unemployment. Figure 8 suggests that there are overall similarities in the behavior of patterns of job separation among the three employment sectors. In particular, in every case, movements into inactivity follow the same procyclical pattern and movements into unemployment the same, although in some cases noisier, counter cyclical pattern. Confirming the average hazard rates reported above, informal jobs are contribute more to the increase in the number of unemployed, particularly during the 1995 recession where the separation rate among the informal salaried is the highest among the three. Also of significance, the key movements during the 1995 recession out of formal employment were emphatically not directly into the informal sector, but into unemployment. In fact, recalling the finding above, entry into informal work from formal work *declines* during downturns, as is the case with transitions among all sectors of informal work. In addition, the probability of moving into unemployment (Figure 8) during the crisis is just below .04 from the formal sector, .06 from self-employment and .13 from informal salaried work. Job separation was largest in the informal sector and accounts for the largest flows into unemployment during the crisis.

Clearly, resolving the tension between this finding of integrated formal and informal sectors with the noted countercyclical movement in the informal employment shares requires substantially deeper understanding of the cyclical dynamics and a more complete description of cyclical adjustment is elaborated in Bosch and Maloney (2005). However, the present exercise suggests that temporal disaggregation offers some of the greatest potential for identifying among different hypotheses about the functioning of LDC labor markets.

V. Conclusion

This paper has employed a common methodology of estimating continuous time Markov processes on panel data from three countries with three purposes. First, we generate a set of stylized facts about LDC labor market dynamics and find a remarkable degree of similarity in sectoral duration and transition patterns across the three countries. Second, we explore the possible uses for and limitations of a set of statistics for drawing inferences from Markov transition matrices. Third, as an example of intrinsic interest in itself, we ask to what degree these statistics can shed light on the nature on reason for being of the informal sector in developing countries. In the process, we highlight problems of heterogeneity and of identification: that transitions statistics have as fundamentally reduced forms that conflate comparative advantage in a sector with ability to enter the sector. We explore additional identification strategies exploiting variation across age, education, gender and time to this end. Overall, we find patterns of transition suggestive that a substantial part of the informal sector, particularly the self-employed, corresponds to voluntary entry although informal salaried work appears may correspond more closely to the standard queuing view, especially for young workers.

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Table 1: Sample Distribution across Sectors and Age and Education Groups.

	All		14-24		24-40		40-60		Low Education		High Education	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Argentina												
OLF	20	52	48	66	3	42	11	51	17	60	23	48
UNM	12	9	14	11	11	9	10	7	15	9	10	9
SE	21	10	5	3	23	12	31	14	20	11	21	10
I	13	9	16	8	14	11	9	9	16	12	10	8
F	35	19	17	12	50	26	38	18	32	8	37	26
	13,866	15,045	4,322	4,211	3,983	4,355	5,561	6,479	5,392	5,683	8,474	9,362
Brazil												
OLF	16	56	24	55	2	50	20	64	16	63	14	41
UNM	4	2	6	5	3	2	2	1	4	2	3	4
SE	20	11	9	5	24	15	28	13	21	12	18	9
I	15	10	18	11	13	11	12	9	14	8	16	15
F	45	20	42	24	58	23	38	13	45	15	49	32
	1,189,651	1,330,537	411,337	455,306	376,590	439,148	383,906	427,538	803,382	906,584	368,451	415,408
Mexico												
OLF	16	61	34	61	3	56	11	67	12	68	22	50
UNM	4	2	5	4	2	2	3	1	4	2	3	3
SE	28	9	13	3	32	11	41	14	33	11	21	7
I	10	6	15	8	8	5	6	4	13	7	5	4
F	42	21	33	24	54	26	40	14	38	13	48	36
	809,754	975,075	283,627	319,009	267,331	337,356	258,796	318,710	481,680	611,718	328,004	363,306

Notes: OLF=Out of the Labor Force, UNM=unemployment, Self=informal self employment, INF=informal salaried, FOR=formal salaried.

Table 2: Posterior Probability of Embeddability Indexes various Ages.

	Argentina		*Brazil*		*Mexico*	
	Male	***Female***	***Male***	***Female***	***Male***	***Female***
All	0.97	1.00	1.00	1.00	1.00	1.00
14-24	0.78	0.82	1.00	1.00	1.00	1.00
24-40	0.38	0.91	1.00	1.00	1.00	1.00
40-60	0.68	1.00	1.00	1.00	1.00	1.00
Low Education	0.20	0.51	1.00	1.00	1.00	1.00
High Education	0.54	1.00	1.00	1.00	1.00	1.00

Computations are based on 10.000 Monte Carlo draws

Table 3a: Intensity Matrix, Duration and Propensity Matrix: Argentina

	Males						Females				
	Intensity Matrix										
	OLF	*UNM*	*SE*	*I*	*F*		*OLF*	*UNM*	*SE*	*I*	*F*
OLF	-0.390	0.249	0.006	0.106	0.028	*OLF*	-0.311	0.190	0.043	0.063	0.016
	0.014	*0.016*	*0.004*	*0.013*	*0.006*		*0.007*	*0.008*	*0.004*	*0.006*	*0.002*
UNM	0.194	-1.175	0.267	0.546	0.169	*UNM*	0.650	-1.330	0.113	0.444	0.122
	0.016	*0.035*	*0.019*	*0.029*	*0.016*		*0.032*	*0.049*	*0.019*	*0.035*	*0.014*
SE	0.023	0.148	-0.424	0.219	0.034	*SE*	0.230	0.103	-0.655	0.293	0.029
	0.004	*0.013*	*0.015*	*0.014*	*0.005*		*0.016*	*0.019*	*0.023*	*0.021*	*0.006*
I	0.042	0.358	0.258	-0.906	0.247	*I*	0.231	0.283	0.242	-0.899	0.143
	0.007	*0.025*	*0.016*	*0.024*	*0.014*		*0.019*	*0.023*	*0.017*	*0.030*	*0.012*
FOR	0.004	0.089	0.025	0.092	-0.211	*FOR*	0.019	0.070	0.020	0.071	-0.181
	0.002	*0.005*	*0.003*	*0.006*	*0.006*		*0.004*	*0.006*	*0.004*	*0.007*	*0.007*
	Propensity Matrix										
	OLF	*UNM*	*SE*	*I*	*F*		*OLF*	*UNM*	*SE*	*I*	*F*
OLF		0.639	0.016	0.272	0.072	*OLF*		0.610	0.137	0.203	0.050
	0.000	*0.030*	*0.011*	*0.032*	*0.016*			*0.018*	*0.011*	*0.017*	*0.007*
UNM	0.165		0.227	0.464	0.144	*UNM*	0.489		0.085	0.334	0.092
	0.012	*0.000*	*0.015*	*0.019*	*0.013*		*0.018*		*0.013*	*0.022*	*0.009*
SE	0.054	0.349		0.516	0.081	*SE*	0.352	0.157		0.447	0.044
	0.009	*0.027*	*0.000*	*0.028*	*0.011*		*0.024*	*0.025*		*0.024*	*0.010*
I	0.047	0.395	0.285		0.273	*I*	0.257	0.314	0.269		0.159
	0.008	*0.023*	*0.017*	*0.000*	*0.015*		*0.020*	*0.026*	*0.018*		*0.011*
FOR	0.017	0.423	0.121	0.439		*FOR*	0.108	0.389	0.109	0.394	
	0.008	*0.023*	*0.013*	*0.023*	*0.000*		*0.023*	*0.034*	*0.019*	*0.032*	
	Average Duration										
	OLF	*UNM*	*SE*	*I*	*F*		*OLF*	*UNM*	*SE*	*I*	*F*
	2.569	0.852	2.360	1.105	4.750		3.204	0.750	1.533	1.111	5.574
	0.078	*0.029*	*0.078*	*0.033*	*0.147*		*0.071*	*0.027*	*0.048*	*0.035*	*0.246*

Notes: Standard Errors in italics below. Computations are based on 10.000 Monte Carlo draws

Table 3b: Intensity Matrix, Duration and Propensity Matrix: Brazil

	Males						Females				
	Intensity Matrix										
	OLF	*UNM*	*SE*	*I*	*F*		*OLF*	*UNM*	*SE*	*I*	*F*
OLF	-0.420	0.117	0.065	0.137	0.101	*OLF*	-0.221	0.048	0.077	0.056	0.039
	0.001	*0.001*	*0.001*	*0.001*	*0.001*		*0.001*	*0.000*	*0.000*	*0.000*	*0.000*
UNM	0.391	-2.069	0.298	0.588	0.792	*UNM*	0.900	-2.106	0.127	0.470	0.608
	0.004	*0.010*	*0.004*	*0.007*	*0.006*		*0.007*	*0.011*	*0.004*	*0.007*	*0.006*
SE	0.082	0.052	-0.426	0.201	0.091	*SE*	0.429	0.014	-0.649	0.159	0.047
	0.001	*0.001*	*0.001*	*0.001*	*0.001*		*0.002*	*0.001*	*0.002*	*0.002*	*0.001*
I	0.160	0.167	0.308	-1.102	0.468	*I*	0.293	0.132	0.210	-1.348	0.414
	0.002	*0.003*	*0.002*	*0.004*	*0.002*		*0.002*	*0.002*	*0.002*	*0.003*	*0.003*
FOR	0.037	0.079	0.037	0.069	-0.223	*FOR*	0.074	0.060	0.017	0.069	-0.221
	0.000	*0.001*	*0.000*	*0.001*	*0.001*		*0.001*	*0.001*	*0.000*	*0.001*	*0.001*
	Propensity Matrix										
	OLF	*UNM*	*SE*	*I*	*F*		*OLF*	*UNM*	*SE*	*I*	*F*
OLF		0.278	0.155	0.327	0.240	*OLF*		0.220	0.348	0.255	0.177
	0.000	*0.003*	*0.002*	*0.003*	*0.002*			*0.002*	*0.001*	*0.002*	*0.001*
UNM	0.189		0.144	0.284	0.383	*UNM*	0.428		0.061	0.223	0.289
	0.002	*0.000*	*0.002*	*0.003*	*0.002*		*0.003*		*0.002*	*0.003*	*0.003*
SE	0.192	0.123		0.472	0.213	*SE*	0.661	0.022		0.245	0.073
	0.002	*0.002*	*0.000*	*0.003*	*0.002*		*0.002*	*0.002*		*0.002*	*0.001*
I	0.145	0.151	0.279		0.425	*I*	0.279	0.126	0.200		0.395
	0.001	*0.002*	*0.001*	*0.000*	*0.002*		*0.002*	*0.002*	*0.002*		*0.002*
FOR	0.168	0.356	0.167	0.310		*FOR*	0.335	0.273	0.079	0.314	
	0.001	*0.002*	*0.001*	*0.002*	*0.000*		*0.003*	*0.003*	*0.001*	*0.002*	
	Average Duration										
	OLF	*UNM*	*SE*	*I*	*F*		*OLF*	*UNM*	*SE*	*I*	*F*
	2.378	0.483	2.350	0.907	4.482		4.531	0.475	1.540	0.954	4.519
	0.006	*0.002*	*0.008*	*0.003*	*0.012*		*0.012*	*0.003*	*0.005*	*0.003*	*0.016*

Notes: Standard Errors in italics below. Computations are based on 10.000 Monte Carlo draws

Table 3c: Intensity Matrix, Duration and Propensity Matrix: Mexico

Intensity Matrix

	Males						Females				
	OLF	*UNM*	*SE*	*I*	*F*		*OLF*	*UNM*	*SE*	*I*	*F*
OLF	-0.451	0.141	0.035	0.180	0.095	*OLF*	-0.256	0.049	0.064	0.083	0.060
	0.003	*0.003*	*0.001*	*0.003*	*0.002*		*0.001*	*0.001*	*0.001*	*0.001*	*0.001*
UNM	0.580	-2.246	0.222	0.814	0.630	*UNM*	1.330	-2.412	0.051	0.539	0.492
	0.012	*0.024*	*0.008*	*0.016*	*0.012*		*0.017*	*0.025*	*0.007*	*0.016*	*0.011*
SE	0.034	0.026	-0.501	0.265	0.175	*SE*	0.530	0.007	-0.759	0.180	0.042
	0.001	*0.001*	*0.002*	*0.002*	*0.001*		*0.004*	*0.002*	*0.004*	*0.003*	*0.002*
I	0.099	0.099	0.259	-0.869	0.412	*I*	0.464	0.090	0.139	-1.056	0.362
	0.001	*0.002*	*0.002*	*0.003*	*0.002*		*0.003*	*0.003*	*0.002*	*0.005*	*0.003*
FOR	0.023	0.045	0.055	0.093	-0.216	*FOR*	0.080	0.035	0.019	0.115	-0.248
	0.000	*0.001*	*0.000*	*0.001*	*0.001*		*0.001*	*0.001*	*0.001*	*0.001*	*0.001*

Propensity Matrix

	OLF	*UNM*	*SE*	*I*	*F*		*OLF*	*UNM*	*SE*	*I*	*F*
OLF		0.313	0.077	0.399	0.211	*OLF*		0.190	0.251	0.323	0.236
	0.000	*0.005*	*0.002*	*0.005*	*0.004*			*0.002*	*0.002*	*0.003*	*0.002*
UNM	0.258		0.099	0.363	0.280	*UNM*	0.552		0.021	0.223	0.204
	0.004	*0.000*	*0.004*	*0.006*	*0.005*		*0.006*		*0.002*	*0.005*	*0.004*
SE	0.068	0.052		0.530	0.349	*SE*	0.697	0.009		0.238	0.056
	0.002	*0.002*	*0.000*	*0.003*	*0.003*		*0.003*	*0.002*		*0.004*	*0.002*
I	0.114	0.114	0.298		0.474	*I*	0.440	0.085	0.132		0.344
	0.002	*0.002*	*0.002*	*0.000*	*0.002*		*0.003*	*0.003*	*0.002*		*0.003*
FOR	0.107	0.209	0.252	0.432		*FOR*	0.322	0.140	0.078	0.461	
	0.002	*0.003*	*0.002*	*0.003*	*0.000*		*0.003*	*0.003*	*0.002*	*0.004*	

Average Duration

	OLF	*UNM*	*SE*	*I*	*F*		*OLF*	*UNM*	*SE*	*I*	*F*
	2.218	0.445	1.996	1.151	4.620		3.906	0.414	1.318	0.948	4.025
	0.012	*0.005*	*0.008*	*0.004*	*0.017*		*0.013*	*0.004*	*0.008*	*0.004*	*0.021*

Notes: Standard Errors in italics below. Computations are based on 10.000 Monte Carlo draws

Table 4: Mobility Indexes various Ages.

	Argentina		*Brazil*		*Mexico*	
	Male	***Female***	***Male***	***Female***	***Male***	***Female***
All	0.621	0.675	0.848	0.909	0.857	0.946
	0.0111	*0.0132*	*0.0057*	*0.0068*	*0.0037*	*0.0042*
14-24						
	0.7676	0.8533	0.9430	0.9908	0.9108	0.9740
	0.0262	*0.0403*	*0.0116*	*0.0132*	*0.0055*	*0.0064*
24-40						
	0.6915	0.7667	0.7883	0.8360	0.8629	0.8888
	0.0273	*0.0268*	*0.0110*	*0.0114*	*0.0080*	*0.0089*
40-60						
	0.5985	0.6653	0.6946	0.8342	0.8363	0.9054
	0.0180	*0.0195*	*0.0112*	*0.0209*	*0.0077*	*0.0115*
Low Education						
	0.6518	0.7665	0.7811	0.8919	0.8512	0.9383
	0.0172	*0.0239*	*0.0077*	*0.0104*	*0.0050*	*0.0068*
High Education						
	0.6155	0.6808	0.6978	0.7104	0.8374	0.8957
	0.0140	*0.0163*	*0.0089*	*0.0099*	*0.0059*	*0.0063*

Notes: Computations are based on 10.000 Monte Carlo draws Standard Errors below

Table 5: Intensity Matrix, Duration and Propensity Matrix for Single Females: Argentina and Mexico

Intensity Matrix	***Argentina***					***Intensity Matrix***	***Mexico***				
	OLF	*UNM*	*SELF*	*INF*	*FOR*		*OLF*	*UNM*	*SELF*	*INF*	*FOR*
OLF	-0.398	0.282	0.013	0.065	0.038	*OLF*	-0.357	0.146	0.039	0.085	0.087
	0.014	*0.016*	*0.005*	*0.009*	*0.006*		*0.002*	*0.002*	*0.001*	*0.001*	*0.001*
UNM	0.466	-1.086	0.075	0.360	0.185	*UNM*	1.118	-2.052	0.098	0.305	0.531
	0.038	*0.059*	*0.020*	*0.042*	*0.024*		*0.019*	*0.025*	*0.007*	*0.012*	*0.012*
SE	0.135	0.183	-0.762	0.363	0.080	*SE*	0.274	0.048	-0.590	0.178	0.091
	0.037	*0.052*	*0.066*	*0.059*	*0.025*		*0.006*	*0.005*	*0.007*	*0.005*	*0.004*
I	0.157	0.395	0.185	-0.876	0.139	*I*	0.291	0.110	0.116	-0.889	0.371
	0.031	*0.049*	*0.029*	*0.053*	*0.023*		*0.006*	*0.005*	*0.003*	*0.008*	*0.005*
F	0.015	0.097	0.021	0.053	-0.186	*F*	0.070	0.052	0.015	0.074	-0.211
	0.007	*0.013*	*0.006*	*0.010*	*0.012*		*0.001*	*0.001*	*0.001*	*0.001*	*0.002*
Propensity Matrix						***Propensity Matrix***					
	OLF	*UNM*	*SELF*	*INF*	*FOR*		*OLF*	*UNM*	*SELF*	*INF*	*FOR*
OLF		0.706	0.032	0.164	0.098	*OLF*		0.409	0.109	0.239	0.243
		0.031	*0.013*	*0.026*	*0.016*			*0.005*	*0.002*	*0.004*	*0.004*
UNM	0.430		0.069	0.331	0.170	*UNM*	0.545		0.048	0.149	0.259
	0.029		*0.019*	*0.032*	*0.021*		*0.006*		*0.003*	*0.006*	*0.005*
SE	0.178	0.241		0.477	0.105	*SE*	0.464	0.081		0.302	0.154
	0.047	*0.066*		*0.063*	*0.033*		*0.009*	*0.008*		*0.008*	*0.006*
I	0.179	0.450	0.212		0.159	*I*	0.328	0.124	0.130		0.418
	0.035	*0.047*	*0.030*		*0.026*		*0.006*	*0.006*	*0.004*		*0.005*
F	0.081	0.522	0.113	0.284		*F*	0.334	0.246	0.070	0.349	
	0.037	*0.060*	*0.032*	*0.051*			*0.006*	*0.006*	*0.003*	*0.005*	
Average Duration						***Duration***					
	OLF	*UNM*	*SELF*	*INF*	*FOR*		*OLF*	*UNM*	*SELF*	*INF*	*FOR*
	2.512	0.924	1.322	1.145	5.408		2.801	0.488	1.696	1.125	4.750
	0.110	*0.050*	*0.114*	*0.069*	*0.362*		*0.021*	*0.006*	*0.021*	*0.010*	*0.038*

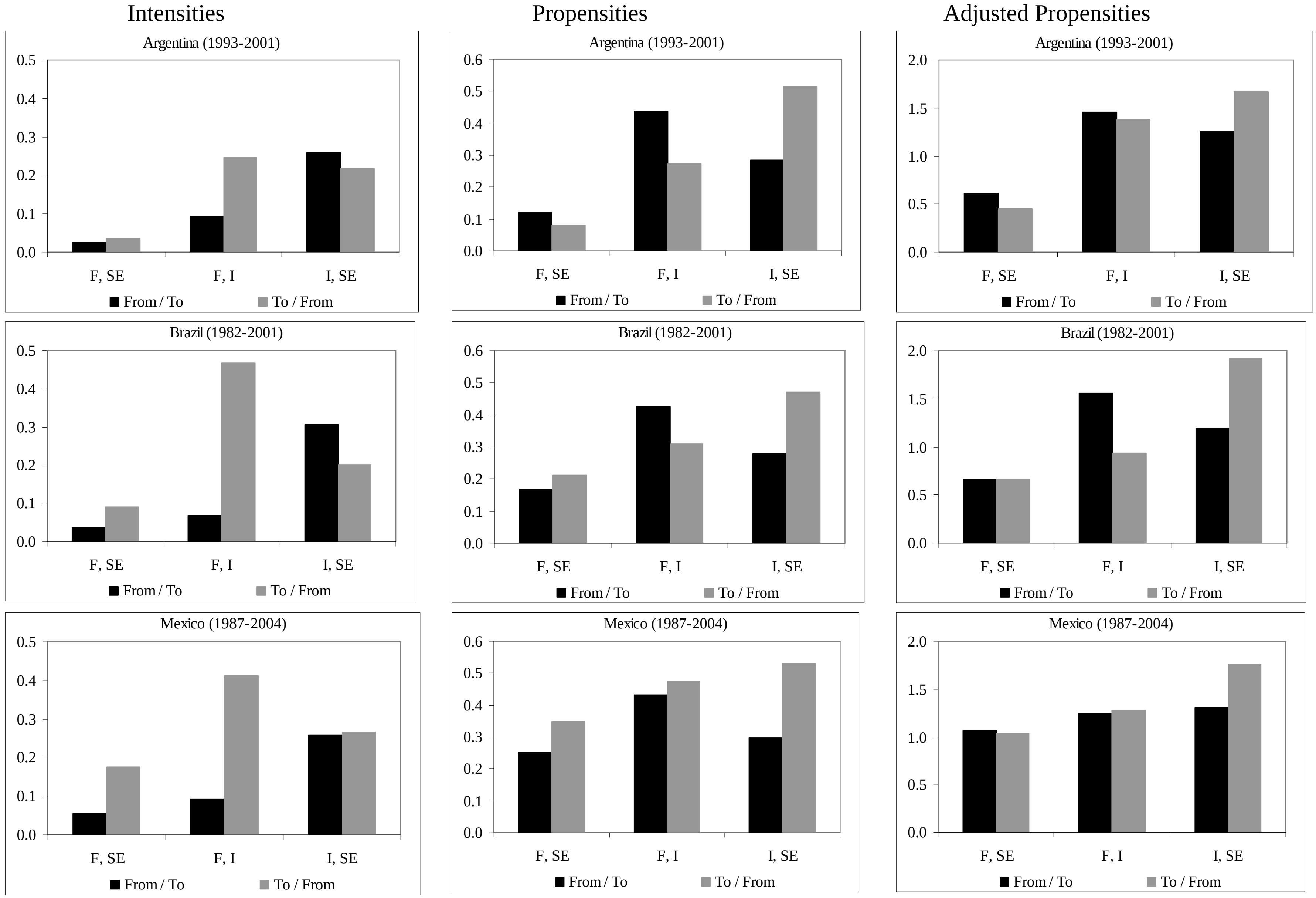
Notes: Standard Errors in italics below. Computations are based on 10.000 Monte Carlo

Table 6: New Unemployed by Sector of Origin

	Self-Employment	*Informal Salaried*	*Formal Salaried*
Argentina	31%	35%	34%
Brazil	15%	24%	61%
Mexico	28%	22%	49%

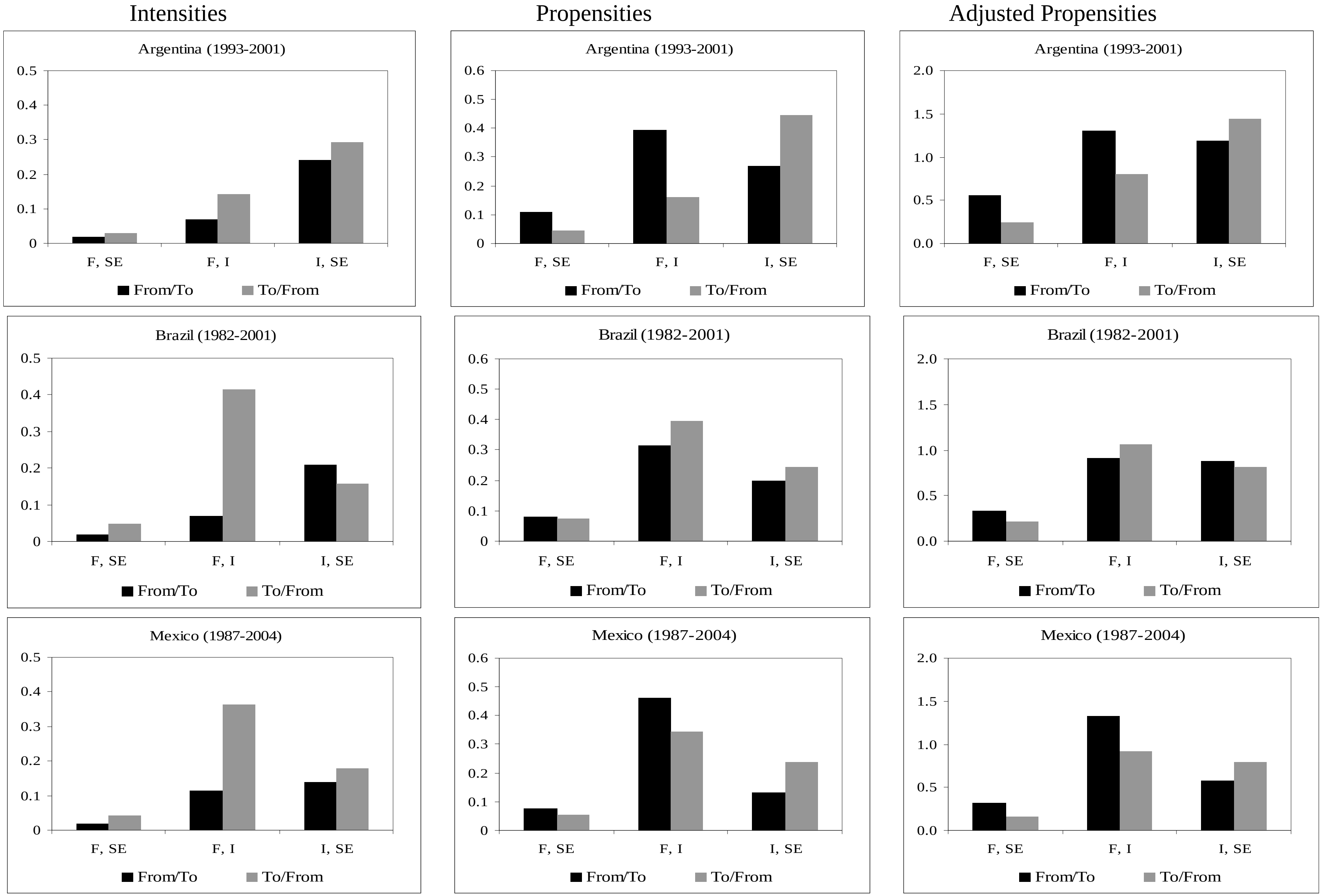
The results were computed using original sector sizes and the estimated intensities to calculate flows into unemployment

Figure 1a: Intensities, Propensities and Adjusted Propensities among sectors (Males)



Notes: Figure represent probabilities of transition among the Formal (F), Self employed (SE) and Informal Salaried (I) sectors. The Intensities correspond to raw instantaneous probabilities; the Propensities standardize the intensities by the instantaneous probability of leaving the initial sector; the Adjusted Propensities further adjust by the availability of positions in the final sector and constitute a measure of revealed comparative advantage.

.Figure 1b: Intensities, Propensities and Adjusted Propensities among sectors (Females)



Notes: Figure represent probabilities of transition among the Formal (F), Self employed (SE) and Informal Salaried (I) sectors. The Intensities correspond to raw instantaneous probabilities; the Propensities standardize the intensities by the instantaneous probability of leaving the initial sector; the Adjusted Propensities further adjust by the availability of positions in the final sector and constitute a measure of revealed comparative advantage.

Figure 2: Absolute Mean Duration in Each Sector in Years

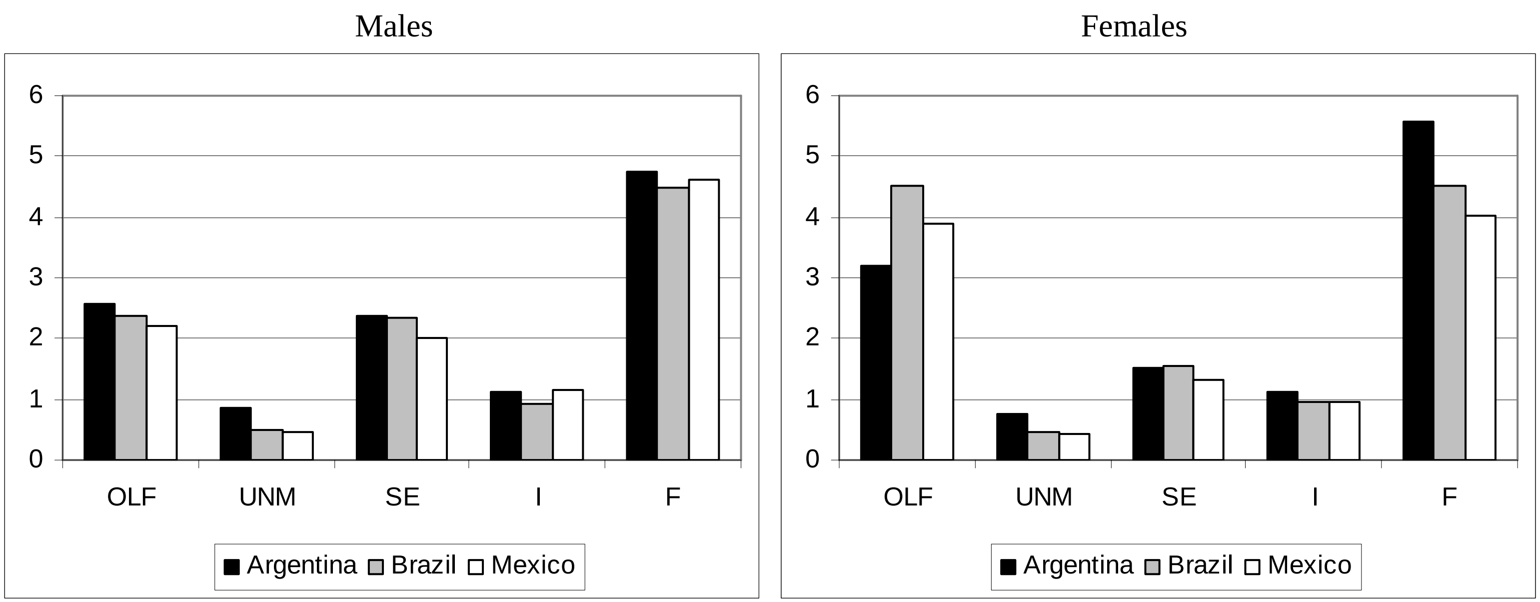
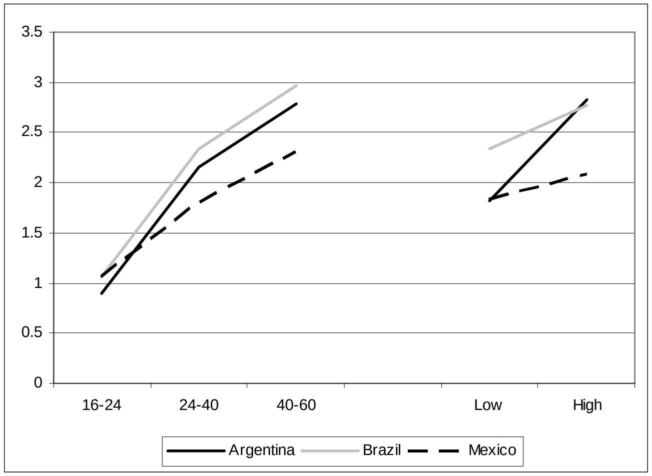


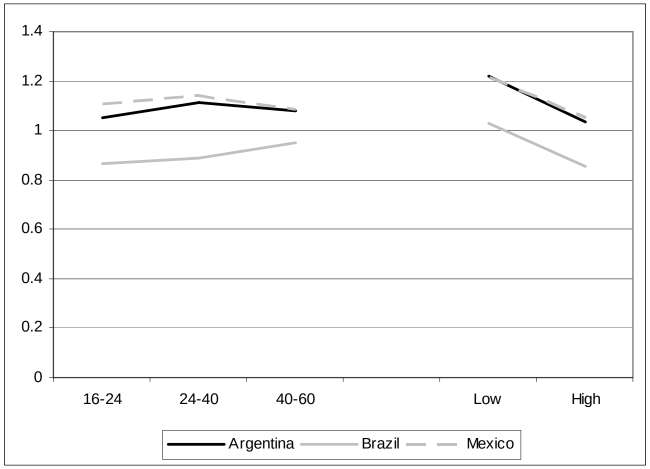
Figure 3a: Mean Duration in Employment Statues by Age and Education in non Employment Sectors (in Years).

Figure 3b: Mean Duration in Employment Statues by Age and Education in Employment Sectors (in Years).

Self-Employment



Informal Salaried



Formal Salaried

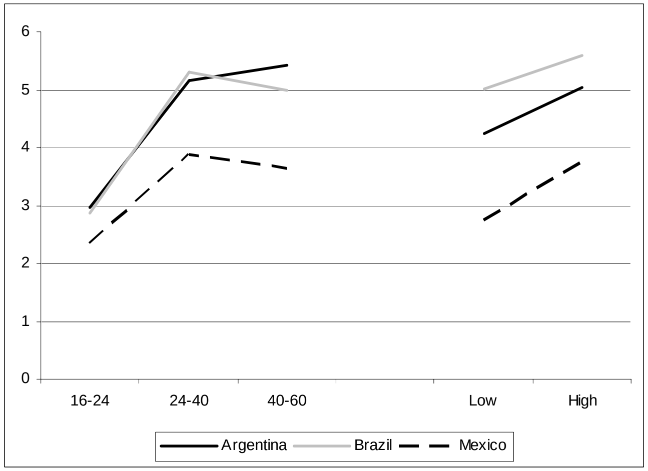
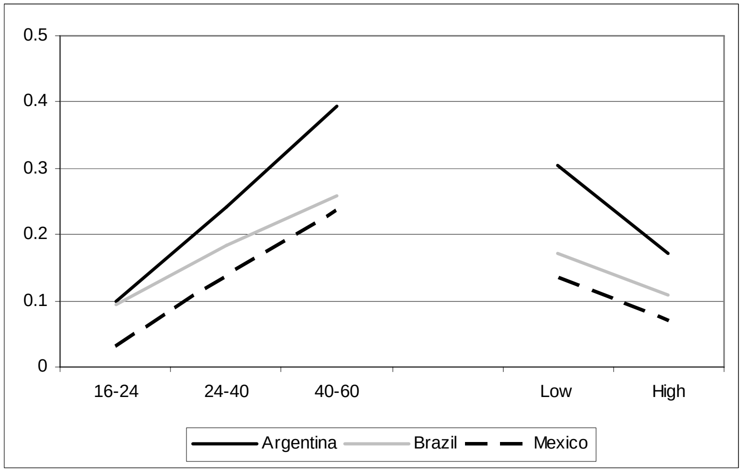
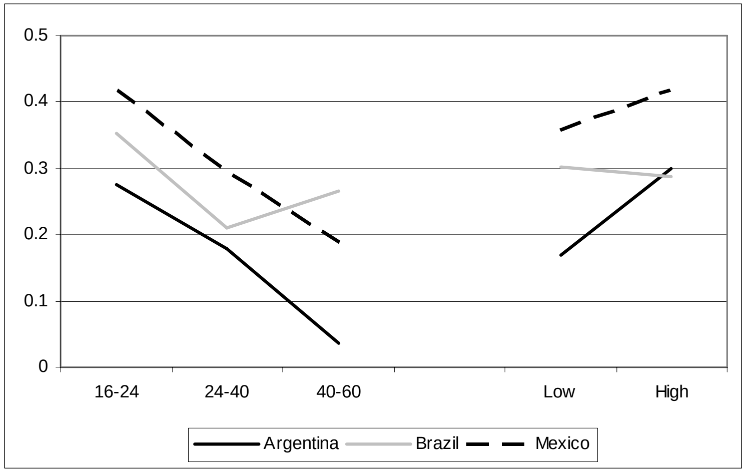


Figure 4a Propensities into Employment from OLF by Age and Educational group

Self-Employment



Informal Salaried



Formal Salaried

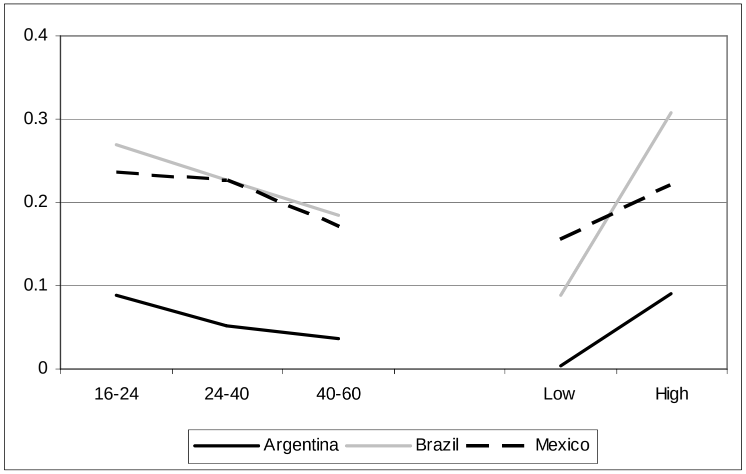
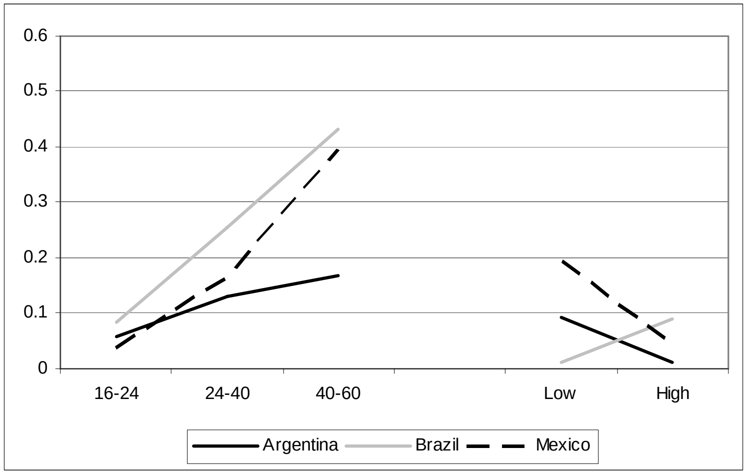
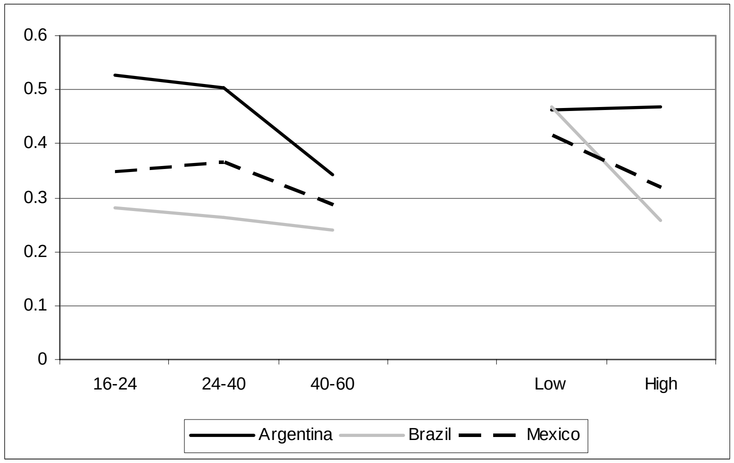


Figure 4b Propensities into Employment from Unemployment by Age and Educational group

Self-Employment



Informal Salaried



Formal Salaried

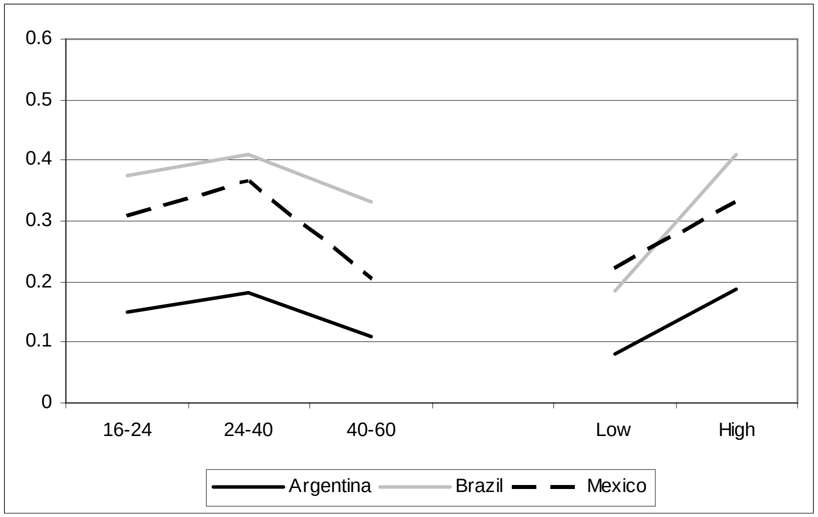
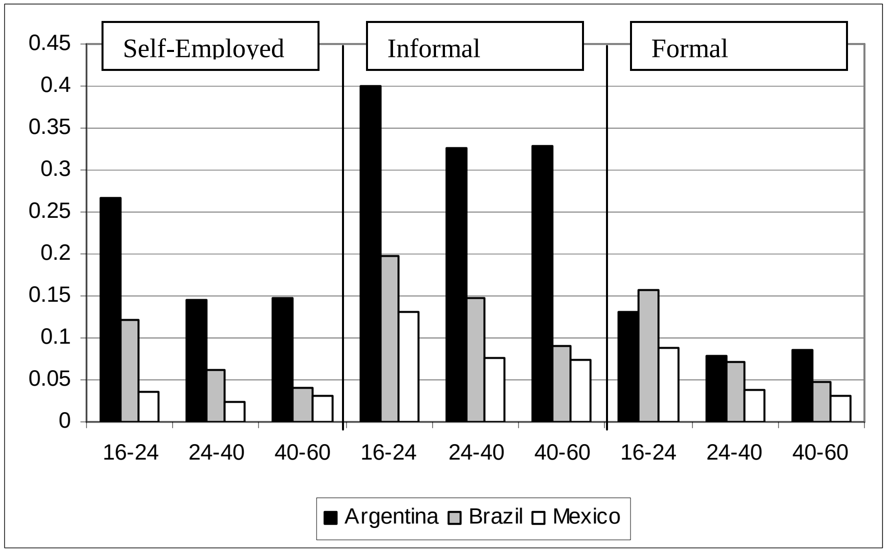


Figure 5a: Separation intensities by Age Group

Towards Unemployment



Towards OLF

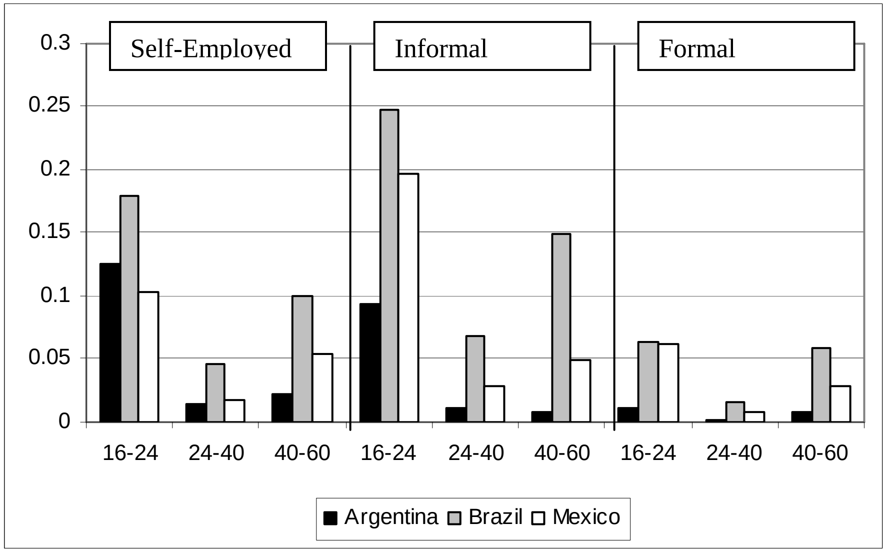
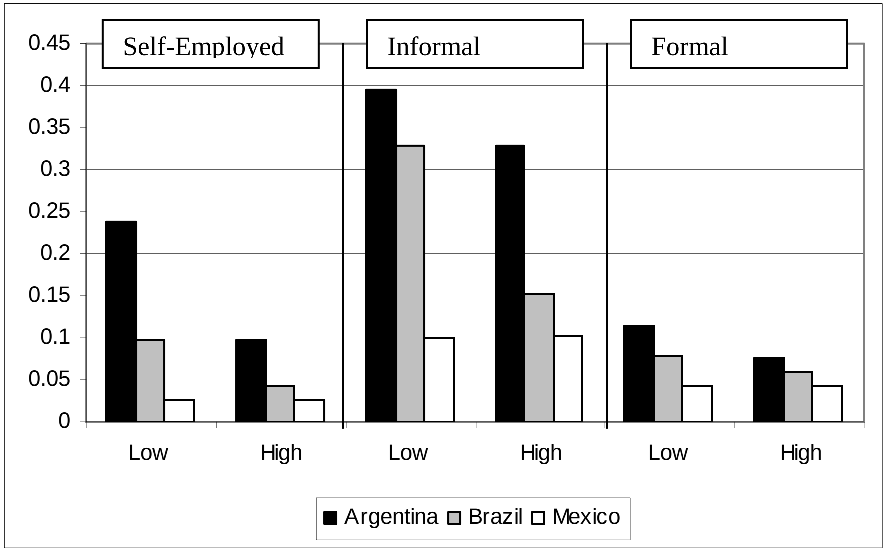


Figure 5b: Separation intensities by Educational Group

Towards Unemployment



Towards OLF

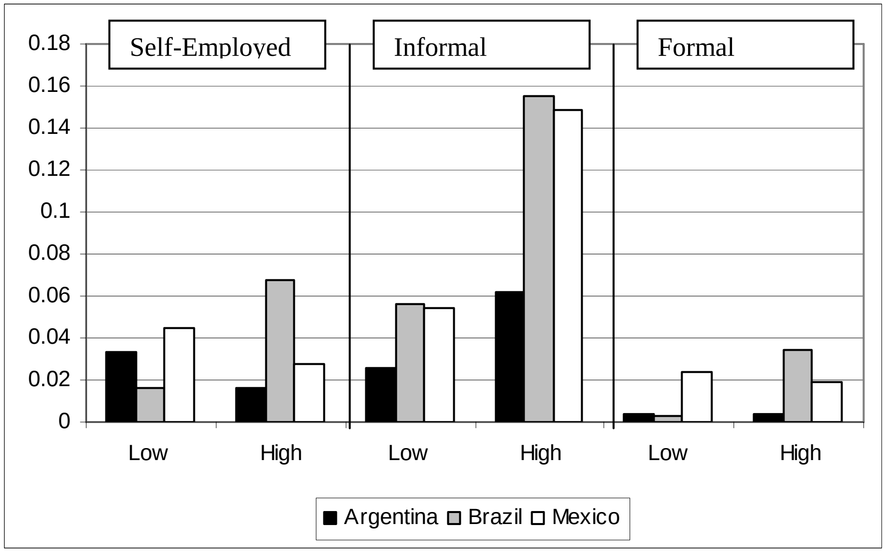
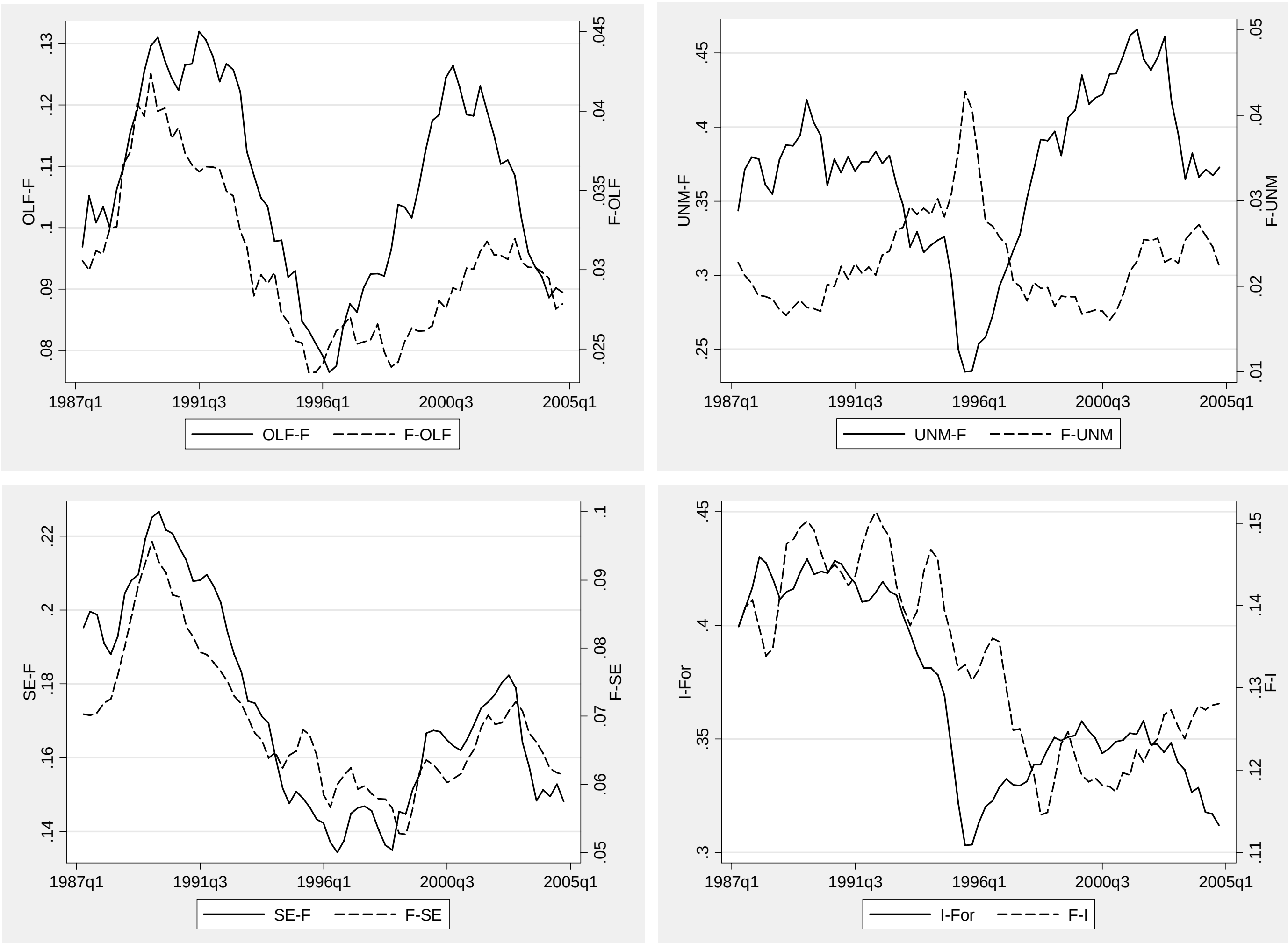


Figure 6: Shares of Formal Informal Sector and Unemployment.

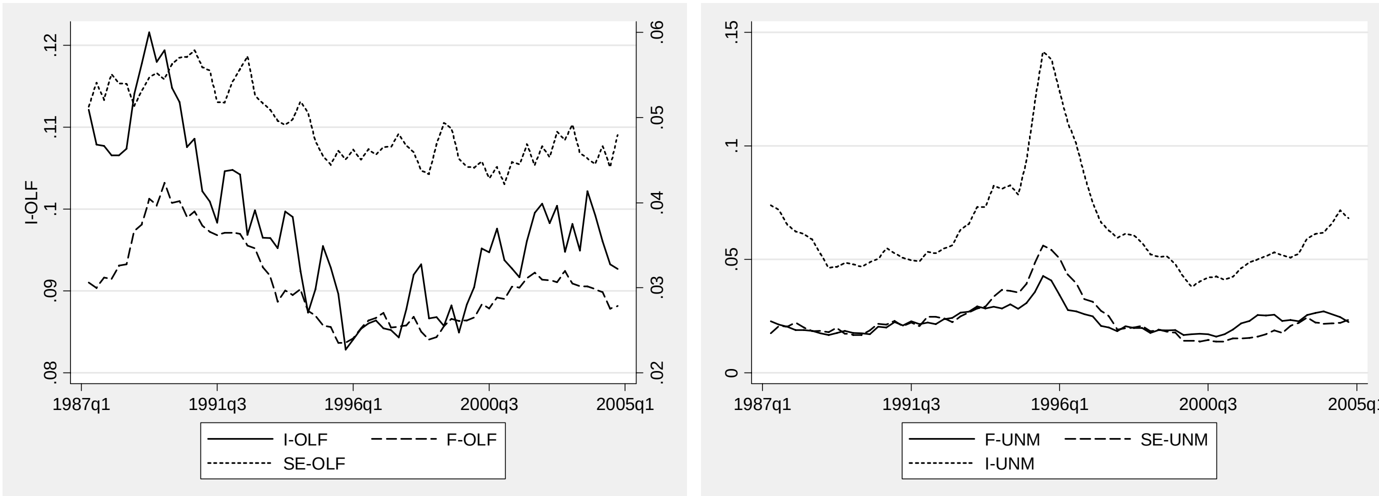
Notes: Constructed with quarterly data from the National Urban Labor Survey (ENEU). % For is the share of formal employment constructed as number of formal workers over total employment. Unemployment rate (Unem. Rate) corresponds to number of unemployed workers over total labor force. The series have been smoothed using a moving average filter with a three quarter window.

Figure 7: Transitions In and Out Formal Employment



Notes: Transition rates among sectors rates inferred from the continuous time transition matrix for each period using quarterly data from the National Urban Labor Survey (ENEU) 1987:Q1 to 2004:Q4 following the procedure by Geweke et al. (1986) outlined in section II. Computations are based on 10.000 Monte Carlo replications. OLF=Out of the Labor Force, UNM=Unemployment rate, I=Informal Salaried, SE=Informal Self-employed, F=Formal Sector.

Figure 8: Separation rates



Notes: Transition rates among sectors rates inferred from the continuous time transition matrix for each period using quarterly data from the National Urban Labor Survey (ENEU) 1987:Q1 to 2004:Q4 following the procedure by Geweke et al. (1986) outlined in section II. Computations are based on 10.000 Monte Carlo replications. OLF=Out of the Labor Force, UNM=Unemployment rate, I=Informal Salaried, SE=Informal Self-employed, F=Formal Sector