DOCUMENTO DE TRABAJO N° 334

# EXPLAINING THE TRANSITION PROBABILITIES IN THE PERUVIAN LABOR MARKET

**José Rodríguez y Gabriel Rodríguez**

DEPARTAMENTO DE **ECONOMÍA**

PONTIFICIA **UNIVERSIDAD CATÓLICA** DEL PERÚ

DOCUMENTO DE TRABAJO N° 334

**EXPLAINIG THE TRANSITION PROBABILITIES IN THE PERUVIAN LABOR MARKET**

José Rodríguez y Gabriel Rodríguez

Agosto, 2012

DEPARTAMENTO
DE **ECONOMÍA**

PONTIFICIA
UNIVERSIDAD
CATÓLICA
DEL PERÚ

DOCUMENTO DE TRABAJO 334
http://www.pucp.edu.pe/departamento/economia/images/documentos/DDD334.pdf

Av. Universitaria 1801, Lima 32 – Perú.
Teléfono: (51-1) 626-2000 anexos 4950 - 4951
Fax: (51-1) 626-2874
econo@pucp.edu.pe
www.pucp.edu.pe/departamento/economia/

Encargado de la Serie: Luis García Núñez
Departamento de Economía – Pontificia Universidad Católica del Perú,
lgarcia@pucp.edu.pe

José Rodríguez y Gabriel Rodríguez

Explaining the Transition Probabilities in the Peruvian Labor Market.
Lima, Departamento de Economía, 2012
(Documento de Trabajo 334)

PALABRAS CLAVE: Markovian transition probabilities, Peruvian labor markets logit models, employment.



Hecho el Depósito Legal en la Biblioteca Nacional del Perú Nº 2012-10503
ISSN 2079-8466 (Impresa)
ISSN 2079-8474 (En línea)

Impreso en Cartolán Editora y Comercializadora E.I.R.L.
Pasaje Atlántida 113, Lima 1, Perú.
Tiraje: 100 ejemplares

# EXPLAINING THE TRANSITION PROBABILITIES IN THE PERUVIAN LABOR MARKET

José Rodríguez
Gabriel Rodríguez


## RESUMEN

El estudio tiene 2 objetivos. Primero establecer las principales características de la movilidad laboral; segundo analizar los determinantes de las principales transiciones entre los distintos estados de la ocupación. Para lograr el primer objetivo se utiliza matrices de transición que permiten analizar la dinámica de los mercados laborales y establecer los hechos estilizados de la movilidad laboral. Con relación al segundo objetivo, se ha modelado la pérdida de la ocupación utilizando regresiones logit de manera de poder identificar la importancia tanto de factores de demanda como de oferta. Para esto se utilizan muestras panel de las encuestas de hogares del período 2007-2010.

Los resultados indican que existe un importante grado de movilidad entre los distintos estados, pero a nivel agregado estos movimientos tienden a cancelarse, con lo cual la distribución de la población a lo largo del tiempo en esos estados permanece constante. Con relación a la pérdida de ocupación, se ha logrado capturar el importante rol que cumplen las condiciones demanda.

## ABSTRACT

This study has two aims. First, to establish the main features of labor mobility; and second, to analyze the determinants of the main transitions between states of occupation. In order to achieve the first objective, we utilize transition matrices, on the basis of which different indicators are calculated that allow the characterization of the dynamics of labor markets in Peru. These calculations, in addition to the results of previous works, enable us to establish a number of stylized facts about labor mobility. Regarding the second objective, and having identified the loss of occupation as one of the most important transitions, an analysis of logit regression is performed in order to establish the correlation between supply and demand factors and the probability of staying occupied or losing that status. Panel samples of household surveys on a national scale for the period 2007-2010 are employed.

The results indicate that there is an important degree of mobility where important proportions of the population switch between states, but in aggregate these transitions tend to cancel out. With respect to the determinants of the transition, the important role of labor demand has been identified; it was captured with levels in employment and their changes in time.

**Keywords:** Markovian transition probabilities, Peruvian labor markets, logit models, employment
**JEL codes:** J21, J23, J60, J62

# EXPLAINING THE TRANSITION PROBABILITIES IN THE PERUVIAN LABOR MARKET [1]

José Rodríguez[2]
Gabriel Rodríguez[3]

## 1. INTRODUCTION

An analysis of labor markets using cross-sectional data shows only one part of what takes place in the labor environment. For example, in spite of the strong growth of the Peruvian economy in the last decade, neither the rate of unemployment nor the rate of activity have changed significantly. In net terms, the creation of jobs (salaried and non-salaried, which is very important in Peru) has been significant, but only in the last years have labor incomes shown a recovery in real terms. However, the participation of informal employment in most of the decade hasn't practically changed (Rodríguez and Higa, 2010). On the other hand, the relatively scarce and recent information from panel samples has made it possible to notice that gross flows of population in working age between economic activity and inactivity, and between occupation and non-occupation (which is not necessarily the same thing as unemployment) are very important.

The scant literature that investigates the labor dynamics by using panel samples has already pointed out that there is a high degree of labor mobility (Chacaltana 2001, Díaz and Maruyama 2000, Herrera and Hidalgo 2002, Herrera and Rosas 2003, and Morales et al. 2010). There are results of measurements of labor transitions on a national scale, for urban and rural areas in separate, and even for the Lima Metropolitan Area which encompasses more than a fourth of the country's population. As a whole,

1 We thank Jorge Luis Bazan for the support he provided us with the use of Winbugs. We are also grateful to Rosibell Solis who supported us with the databases. This work was possible thanks to financial support from the Pontificia Universidad Católica del Perú.
2 Address for correspondence: José S. Rodríguez, Department of Economics, Pontificia Universidad Católica del Perú, Av. Universitaria 1801, Lima 32, Lima, Perú, telephone +511-6262000 (5385), fax +511-6262874. Email: jrodrig@pucp.edu.pe.
3 Department of Economics, Pontificia Universidad Católica del Perú, Av. Universitaria 1801, Lima 32, Lima, Perú, telephone +511-6262000 (4998), fax +511-6262874. E-mail: Gabriel.rodriguez@pucp.edu.pe.

and considering 3 states (occupied, non-occupied and inactive) on a national scale, for example by using yearly panels, it has been estimated that between 1998 and 2008 an average of 21% of the working age population switched states. In the urban areas of the country, mobility can reach around 20% with quarterly panels, 25%-30% with yearly panels, and even 40% if the joint information of 4 quarterly panels is used along one year.

Another result found in the Peruvian literature is the existence of population flows between occupation and inactivity in both directions that are vastly larger than the flows between occupation and unemployment. This is explained (or is at least associated) by the fact that the share of population that is unemployed is relatively small (4%-5% on a national scale) and by the fact that the duration of unemployment is relatively short (Chacaltana 2001 and Díaz and Maruyama 2000).

Regarding high mobility, it is interesting to mention some results from other countries. For example, for the Chilean case, García and Naudon (2012) found, by using quarterly panels between 1993 and 2009, that on average 12.9% of the working age population (15 years and older) switches states between occupation, unemployment and inactivity. For the case of Argentina, Pessino and Andrés (2000) report results that enable to calculate that 20.6% of the working age population (15 to 64 years) in Gran Buenos Aires switched states between October 1998 and October 1999. If a panel with a shorter inter-period span of 6 months is considered (i.e. October 1998 to May 1999), the degree of mobility remains practically unchanged (20.4%). Regarding the more specific analysis of transitions between states, Pessino and Andrés (2000) report that 57% of the persons that stop being occupied become unemployed in the next period, and the remaining 43% become inactive. The inactive that leave that status change more frequently into occupation (60%) than into unemployment (40%). These authors report the results for the USA and show a different picture than Argentina. For the occupied that change state, the most frequent destination is inactivity (87%), whereas those that leave inactivity have employment as the main destination (89%). The Chilean case also shows that the flows between occupation and inactivity are more important than between occupation and unemployment. This is a feature that is also observed in Peru.

Other studies have analyzed the labor mobility including, in addition to the three states mentioned earlier, a further disaggregation of the occupied into types of employment, typically differentiating between the formal and the informal sectors (see for example Bosch and Maloney 2005 and 2010). They find higher degrees of mobility in comparison with those mentioned above, which are due in part to the fact that more states in transitions are considered. An interesting aspect of these works is that they find evidence that at least part of informal employment can be seen a voluntary employment. Other works only analyze transitions between occupied by placing emphasis in the possible segmentation of the labor markets between formal and informal jobs (see Sedlacek et al 1990, da Silva and Pero 2009). These works show that the time of permanence in informal jobs is much lower than the time of permanence in formal jobs.

The results of the above mentioned literature suggest that it is important to complement the use of cross-sectional data when looking at labor markets, with information that allows an approximation to their dynamics. This work does that, by making intensive use of panel data between 2007 and 2010 for Peru as a whole, initially in order to identify the stylized facts by using transition matrices. We use Bayesian statistics in order to estimate the transition matrices and confidence intervals. With these probabilities we calculate several mobility indices that allow us to characterize the degree, type and intensity of mobility between states. Then we model by using logit regressions what we consider the two most important transitions: occupation - occupation vs. occupation - non-occupation. This exercise, which is carried out separately for men and women, includes variables linked to labor supply, as well as variables that attempt to captures the aggregate movements in labor markets from the demand side. Before presenting our research, we provide in the following section a survey of the results of all the studies on labor mobility that there are in Peru.

In the third section, we attempt to establish the stylized facts regarding labor mobility by using transition matrices and Bayesian statistics. In section 4 the results of an analysis of the determinants of transitions between occupation and non-occupation are presented, by using panel data with binomial logit regressions. The last section provides a balance and conclusions.

## 2. LITERATURE REVIEW FOR THE CASE OF PERU

There are relatively few studies on Peru that analyze labor mobility by using longitudinal information from panel samples[4]. The majority focuses on the second half of the nineties and the early 2000s, and only one study, more recent, covers 2008. This is so in part because there haven't been many samples of this kind in the past. The first studies with household panel samples reach back to the second half of the 1990s. On a national scale, the National Household Survey (ENAHO) was the first that incorporated a household panel sample, but the sample design has changed with time.

### 2.1 A note on the databases

The panel samples used in these works have different features, which limits the possibility of comparing results. The samples differ due to two motives: differences in the geographical coverage (i.e. national, urban Peru, rural Peru and Lima Metropolitan Area), and differences in the sample design itself, which is reflected, among other things, in the time between interviews and the number of times that a person is interviewed along the panel samples. Regarding this last point, we can identify three types of sample designs: (i) interviews every three months throughout a single year (ENAHO Panel 1996), (ii) interviews every three months with continuous samples every month for almost two years (EPE 2001-2002), (iii) interviews every 12 months with samples collected along the last quarter of the year (ENAHO 1997-1998-1999), and (iv) interviews every 12 months with continuous yearly samples (ENAHO 2004-2008).

---

[4] MTPE (1998), Díaz and Maruyama (2000), Chacaltana (2001), Herrera and Hidalgo (2002), Herrera and Rosas (2003) and Morales et al. (2010).

In the first and second types of sample design, the persons were interviewed every three months. In the first case (i.e. ENAHO 1996), this was done throughout 1996 in four opportunities (one interview each quarter), whereas in the second case (i.e. EPE 2001-2002) a group was interviewed in up to four occasions and the other in only two opportunities[5]. In any case, the window of observation for each individual extended for up to nine months, in four opportunities and with intervals of three months between observations.

In types 3 and 4 of panel sample, each person was interviewed two times with an interval between interviews of approximately 12 months. In the 1997, 1998 and 1999 ENAHO surveys, the sample (total and panel) was interviewed during the last semester of each year (October to December), whereas in the 2004-2008 ENAHO surveys, the samples were continuous during the whole year (January to December). These differences in sample distribution throughout the year could lead to bias in the fourth quarter samples due to some kind of seasonality. In any of these two types of sampling, the distance between observations is twelve months.

Finally, the reference population in all ENAHO surveys is Peru on a national scale, whereas for the EPE surveys the reference population is Lima metropolitan area. In spite of these feature of ENAHO surveys, some works were restricted to Urban Peru (Diaz and Maruyama, 2000, and Chacaltana, 2001), whereas others separated the analyses distinguishing between urban and rural areas (Herrera and Rosas, 2003).

[5] See a description of the sampling in http://www.eclac.cl/deype/mecovi/docs/TALLER8/10.pdf and http://www.eclac.cl/deype/mecovi/docs/TALLER9/21.pdf for ENAHO 1996 and in Herrera and Hidalgo (2002) for the EPE 2001-2002. In both cases, there was an increase in the non-response rate over time, which led to a modification of the panel samples design.

## 2.2 Main findings

*(a) Urban Peru*

The work of MTPE (1998), after publication by Chacaltana (2001)[6], is the first study that utilizes the ENAHO 1996 panel sample of four quarters. This same database is utilized by Díaz and Maruyama (2000). Considering three states of working age population (PET) and the focus on the transitions every three months (i.e. first quarter to second, second to third, and third to fourth), approximately 20% of the PET switched state (see Chart 1). In the 80% that didn't change state, the occupied and the inactive are equally important. The individuals that remain inactive during two quarters represent less than 1% of the total. If the window is increased to four quarters in total, the proportion that changes state doubles to 40%. In the remaining 60% that didn't change state, the occupied individuals are over-represented despite the fact that they remain the same proportion of PET (approximately 40%). In other words, the reduction in the percentage of those who didn't change state from 80% to 60% is due to the reduction in those reported as inactive in the four quarters: they drop from 40% of PET in two contiguous quarters to 20% throughout the four quarters. This suggests that an important part of mobility is associated to the group of inactives, for they are presumed to be switching states more frequently in longer periods (in this case up to 9 months).

Even in the range of Urban Peru, Chacaltana (2001) finds in the panel sample of ENAHO of the fourth quarters of 1997 and 1998 (observations with 12 month distances between them), that 27% of PET switched states and 73% didn´t. That is, a higher mobility than observed in the case of surveys every three months (as reported above at around 20%), but lower than the one showed in the set of four quarters in 1996 that points to 40% mobility. At first sight, these results may seem inconsistent, for it is true that after longer periods it seems possible that more people change states, as is suggested by the increase in the proportion that changes states when the

[6] The work of Chacaltana (2001) contains the results reported in MTPE (1998) and expands on them. Although MTPE (1998) doesn't indicate the author, we presume it is Chacaltana.

intervals change from 3 to 12 months. The apparent inconsistency is in the comparison of the result of the three transitions along 2006 with the 12-month transitions, where the first case shows more mobility than the second. We attempt an explanation in the following section.

If mobility along 1996 is defined over the four observations —i.e. one each quarter—, then to not switch states is equivalent to reporting the same state in the four interviews, whereas switching state implies reporting at least one change in any of the three transitions. Since inactivity and unemployment are states with low persistence over time, even despite the fact that being occupied is a very persistent state, it is more likely to find individuals that report changes of state along four observations (with three month of interval between each two of them), than between only two observations with 12 months of distance in between. The reason for it is that, part of those that are reported as inactive at the beginning and the end of the 12 month period (that is, remaining in the same state from this perspective) have transitioned through different states after the initial observation and before the final one. In this sense, the three sets of results with the same database are not inconsistent. What happens is that the measure of mobility is sensitive to the size of the time interval between observations in a context in which there are states of short duration[7].

Herrera and Rosas (2003) disaggregate the analysis of urban Peru by sex and add rural Peru. They employ the panel samples of the last quarters of 1997, 1998 and 1999. They find that mobility is higher in urban than in rural areas, and in women vis-à-vis men. Men in rural areas display the lowest mobility, as 90% of them don’t switch state and most are occupied.

---

[7] Another hypothesis, which could complement the previous one, is that the years 1997 and 1998 may have been better in terms of work opportunities, which would be evident, for example, in more stable jobs. In fact, in the 1997-1998 panel, 54% of PET declared being occupied in both years, in contrast to 40% in 1996.

*(b) Lima metropolitan area*

Herrera and Hidalgo (2002) utilize the EPE survey between March 2001 and December 2002. They stack all panel samples with three month intervals and perform a transition analysis in order to measure vulnerability, as defined by job loss. They find that in the considered period, an average of 22% did switch state. From the 78% that didn't, the most part stayed occupied in the two observations made with intervals of three months only one time.

*(c) National*

Herrera and Rosas (2003) utilize the ENAHO panel survey of the fourth quarters of 1998 and 1999 and find that 27% of the PET switched states and 73% didn't. One more time, the largest part of those who didn't switch states comprised those who reported being occupied in the two years in which they were interviewed. A somewhat different result is reported by Morales et al. (2010), who calculate transition averages using ENAHO from 1998 until 2008. They find that 21% switched states and 79% didn't. Again, among those who didn't switch states in 12 month intervals, the occupied are over-represented.

## 2.3 Summary

Almost all studies assert that in Peru there is high labor mobility, but none of them mention under which criterion this assertion can be made. As has been shown, the proportion of working age population that switches states varies from 10% (men in rural areas) to up to 41% (both sexes in urban areas of Peru). The percentage of population that switches state varies depending on the population scope under consideration (national, urban or rural, Lima metro area) and sex. In metropolitan and urban areas, there is more mobility. Among women, the proportion that switches states is higher than among men in both urban and rural areas.

On the other hand, the period of time elapsed between two panel observations is crucial in measuring mobility. The longer the time elapsed between the two observations, the higher the proportion that switches state, as seems reasonable. The most interesting aspect is that the longer the time lapse, the higher is the proportion of those staying occupied among those that don't switch state in comparison to the inactive, which implies that the latter tend to switch states more often during longer periods.

Finally, the more frequent and important transitions, in relative terms, are those between inactivity and occupation. That is, most of those who leave the status of occupation transition to inactivity, and most of those who stop being inactive change states into being occupied. In other words, unemployment, being active or hidden, doesn't seem to be a transition stage between occupation and inactivity. This is consistent, on the other hand, with the fact that the duration of active unemployment is considered to be low (between 10 and 13 weeks).

**Chart 1**

**Summary of results from studies on labor market transitions in Peru**

| Result of the transition in labor status | Peru urban areas | | | | | | Peru urban areas: men | | | Peru urban areas: women | | | Peru rural areas: men | | | Peru rural areas: women | | | Lima Metro. | Peru | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1996 | 1996 | 1996-1 / 1996-2 | 1996-2 / 1996-3 | 1996-3 / 1996-4 | 1997-4 / 1998-4 | 1997-4 / 1998-4 | 1998-4 / 1999-4 | 1997-4 / 1999-4 | 1997-4 / 1998-4 | 1998-4 / 1999-4 | 1997-4 / 1999-4 | 1997-4 / 1998-4 | 1998-4 / 1999-4 | 1997-4 / 1999-4 | 1997-4 / 1998-4 | 1998-4 / 1999-4 | 1997-4 / 1999-4 | 2001.3 / 2002.12 | 1997-4 / 1998-4 | 1998 al 2008 |
| | (m=3,t=4)[1] | m=3,t=4 | m=3,t=2 | m=3,t=2 | m=3,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=12,t=2 | m=3, t=2 | m=12,t=2 | m=12,t=2 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) |
| Unchanged | 58.8 | 59.2 | 78.6 | 80.7 | 80.5 | 73.2 | 75.9 | 73.9 | 71.3 | 68.6 | 68.1 | 67.4 | 89.8 | 88.9 | 88.3 | 70.9 | 72.3 | 71.3 | 78.4 | 73.3 | 78.7 |
| Occupied | 39.7 | 41.0 | 39.1 | 39.1 | 39.3 | 53.9 | 63.3 | 58.3 | 57.9 | 42.2 | 40.4 | 40.4 | 86.4 | 85.4 | 85.5 | 53.0 | 58.0 | 57.4 | 52.3 | 56.2 | 59.8 |
| Unemployed | 0.1 | 0.0 | 0.7 | 0.5 | 0.3 | 0.9 | 1.7 | 1.6 | 1.1 | 2.3 | 1.7 | 1.8 | 0.1 | 0.0 | 0.3 | 0.9 | 0.5 | 0.7 | 1.6 | 1.4 | 0.5 |
| Inactive | 19.0 | 18.2 | 38.8 | 41.1 | 40.9 | 18.4 | 11.0 | 14.1 | 12.3 | 24.1 | 25.9 | 25.2 | 3.3 | 3.4 | 2.5 | 16.9 | 13.8 | 13.2 | 24.5 | 15.7 | 18.4 |
| Changed | 41.2 | 40.8 | 21.4 | 19.3 | 19.5 | 26.8 | 24.1 | 26.1 | 28.7 | 31.4 | 31.9 | 32.6 | 10.2 | 11.1 | 11.7 | 29.1 | 27.7 | 28.7 | 21.6 | 26.7 | 21.3 |
| Total | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

**Notes**

[1] *m* indicates the number of months elapsed between the first and the last interview, whereas t is the number of times that the same person was interviewed.

**Sources:** Columns 1, 3, 4, 5 and 6: Chacaltana (2001), column 2: Díaz and Maruyama (2000), columns 7 to 18 and 20: Herrera and Hidalgo (2002), column 19: Herrera and Rosas (2003), column 21: Morales et. al. (2010)

# 3. STYLIZED FACTS

We will consider the following distinction within the working age population (PET): those who are occupied and those who aren't. In this second group three types of person can be identified: the open unemployed (those actively looking for jobs in the reference period), the hidden unemployed (those that are discouraged, that is those who have given up searching), and the inactive or persons outside of PEA (because they neither work nor look for a job)[8]. In the methodology that is explained below as well as in the presentation of the stylized facts, the four states of the working age population mentioned above are considered.

## 3.1 Methodology: transition matrices and Bayesian statistics

### 3.1.1. *Transition matrices*

Be ***N*** the matrix that shows the distribution in absolute terms (or quantities) of a certain population according to its state in two periods. Each row in the matrix represents the state in the initial period (t, from now on), and each column the state in the final period ($t+\tau$), in which the length of the interval between two periods can be measured in different units (e.g. days, weeks, months, years). Thus, if the individuals of a panel sample are observed, the time interval between each observation defines the size of $\tau$. In a panel sample with 12 month intervals (such as the panels in the ENAHO survey)[9], and using a time unit of years (t is the calendar year and $\tau$ the number of years between two observations), the initial period is represented by t and the final period by $t+1$.

8 In Peru PET is composed of people aged 14 and more. The official definition of PEA takes only the occupied and the openly unemployed into consideration. So that hidden unemployment is part, under this definition, of inactive PET. The occupied are all those that during the reference period took part in some economic activity that generates some form of income (monetary or otherwise), by working at least one hour per week. The only occupational category that is treated in a different way is that of non-remunerated family workers for which the minimum of working hours in order to be considered occupied is 15 hours in the reference week.

9 Three panels have been made with ENAHO: 1997-2011, 2002-2006, and 2007-2011. From the latter, until now only the database 2007-2010 has been published. In all these panels, the time interval between 2 observations is 12 months.

The number of states is arbitrary but remains the same in each period. In the matrix representation of the population distribution, i (where i = 1, …, s) represents the states in the initial period and j (j= 1, …, s) the states in the final period. In this way, the element $n_{ij}$ represents the number of people that were in state i in the initial period and in state j in the final period.

From matrix ***N*** two more matrices can be defined. The matrix with the relative distribution (i.e. in percentage terms) with respect to the total of the distribution that we will call ***Q*** (and its elements $q_{ij}$); and the transition matrix that represents the population distribution in relation to its initial state, that is, having been in state i in the initial period, how is this population distributed in percentage terms in each of the s states in the final period. We will call this transition matrix ***P*** (and its elements $p_{ij}$). Note that the sum along the rows (columns) of matrix ***Q*** provides the relative (percentage) frequency of each state in the initial (final) period, whereas the sum along the rows of matrix P must be 100%.

*Measures of mobility derived from the matrices*[10]

The degree of total mobility of the population is measured considering all the population that has shown a change in state between the two periods. For example, those that had been occupied in the initial state are observed in the final period as unemployed (in any of its variations) or as inactive (outside of the labor force). Those that stayed in the same state do not represent any mobility. Thus, the total mobility index, which will be denominated ***T***, is equal to the sum of all elements in the matrix ***Q*** (which is 100%), minus the sum of the main diagonal which represents, precisely, the proportion of the total population that was observed in the same state during both periods. Formally:

$$T = \sum \sum_{i,j} q_{ij}, \ for\ i \neq j.$$

Total mobility can be disaggregated into two components. One of them identifies the part of mobility that represents a sort of exchange of persons between two states, in a way that the net flow of people between both states

[10] See Sedlacek et al. (1990) and Zipkin et al. (2010)

is null. For example, if 50 individuals transit from occupation to inactivity and 70 persons from inactivity to occupation, then circular mobility is 100 people: 50 in one direction and 50 in the other. This circular mobility, which we will denominate with ***C***, is measured in proportional terms with respect to the total population. The other component of mobility, instead, measures the excess (or deficit, depending on the direction in the movement of persons) in the flow of persons. Thus, in our example, 20 is the volume of structural mobility, for these 20 people have contributed to modify the relative participation of each state in the total population between the two periods. We denominate this second type of mobility with ***E***[11].

Then, on the basis of these definitions, structural mobility is measured in the following way:

$$E = \sum_i (q_{i\bullet} - q_{\bullet i}) \;\; for \;\; (q_{i\bullet} - q_{\bullet i}) > 0,$$

Where $q_{i\bullet}$ and $q_{\bullet i}$ represent the proportions of the population in state i in the initial and final period, respectively.

Whereas circular mobility is obtained by difference:

$$C = T - E.$$

In addition to these measures of the magnitude of mobility obtained from matrix ***Q***, it is possible to find other indexes by employing matrix *P*. If one assumes that the state of a person in *t* is only dependent of the state in which he or she was in the previous period of *t -1*, then the probability of being in state *j* in the period *m*, having stayed in state *i* in *m-1* previous periods is as follows:

$$f_{ij}^{(m)} = \Pr\{X_m = j, X_{m-1} = i, X_{m-2} = i, \ldots., X_1 = i \,|X_0 = i\} = (p_{ii})^{m-1} p_{ij}$$

11 It must be clear that if, for example, we consider 2 states and all mobility is circular, the relative population distribution between the 2 states in both periods (initial and final) will be exactly the same. This implies that a look on the potential workforce distribution can be very stable in time, and that there is however, a high degree of labor mobility.

Then, the global probability of transitioning from state *i* to state *j* when *m* tends to infinity is:

$$\Pr\{i \to j\} = \sum_{m\to\infty} f_{ij}^{(m)} = \frac{p_{ij}}{1-p_{ii}} .$$

Finally, the expectancy of time that has to pass until an individual stops remaining in state i and switches to any other state $j$ (*j≠i*) is:

$$E[time\ until\ i \to j] = \frac{1}{1-p_{ii}}$$

3.1.2 *Bayesian statistics*

The probabilities or calculated proportions are point estimations whose statistical significance is not possible to evaluate unless recurring to Bayesian techniques. In order to motivate this kind of analysis, consider two random variables A and B. The rules of probability imply that $p(A,B) = p(A/B)\ p(B)$, where $p(A,B)$ is the joint probability of the occurrence of A and B, $p(A/B)$ is the probability that A occurs conditional to the occurrence of B (also known as conditional probability), and $p(B)$ is the marginal probability of B. Alternatively, the roles of A and B can be inverted so that $p(A,B) = p(B/A)$ $p(A)$. By setting both expressions to equal $p(A,B)$ and by ordering terms, we obtain the Bayes rule that is the main foundation of Bayesian econometrics, and which states that $p(B/A) = \frac{p(A/B)p(B)}{p(A)}$.

In our context, the probabilities are the parameters on which we wish to make inference. Take the assumption that the probability or set of probabilities of transition are denoted by the vector $\theta$. What interests us is to know $\theta$ based on the data (y). Using the Bayes rule, we have that $p(\theta/y) = \frac{p(y/\theta)p(\theta)}{p(y)}$. In contrast with classic econometrics, $\theta$ is considered a random variable. Given that we want to find $\theta$, we can ignore p(y) such that we have $p(\theta/y) \propto p(y/\theta)\ p(\theta)$. The term $p(\theta/y)$ is the posterior density of $\theta$; $p(y/\theta)$ is the density of the data given the parameter of the model, also known as the likelihood function. Finally, $p(\theta)$ is the a priori density which does not depend on the data. This density contains any available information on $\theta$ that is not generated from the data, whereas the posterior density is the fundamental focus of interest of this kind of econometrics. This density summarizes all that is known about $\theta$ after the data is observed. This rule indicates that new data or new information allow us to update our beliefs regarding $\theta$. Thus, the posterior density combines information of the data and also a priori information that is independent of data. In all this process, it is important to mention that the election of the a priori density can affect the results of the posterior density. Additionally, in the choice of *a priori* density, it is usual to place emphasis on the values of the mean and variance.

Diverse information such as the moments of the posterior distribution can be used in order to make inference. For example, one might be interested in computing the mean of the posterior density as a point estimator. As before, it is assumed that $\theta$ is a vector with *k* elements. The posterior mean of any element $\theta$ is calculated using $E(\theta_i / y) = \int \theta_i p(\theta / y) d\theta$. With the exception of very simple cases, this integral cannot be evaluated analytically, which leads to an intensive use of computation. Another example is the fact that usually a measure of the degree of uncertainty associated to the point estimator is presented. Such a measure is the posterior standard deviation, which requires the calculation of $E(\theta_i^2 / y) = \int \theta_i^2 p(\theta / y) d\theta$. In general, there are many other such measures that can be presented, which can be summarized in $E[g(\theta) / y] = \int g(\theta) p(\theta / y) d\theta$. The way to find the mentioned measures requires posterior simulation. Although there are plenty of posterior simulators, all of them are applications or extensions of the law of great numbers or the central limit theorem. A direct implication of this fact is what is called Monte Carlo integration, which stipulates that if we have $\theta^{(s)}$ for *s = 1, 2 , ... , S*, a random sample obtained from $p(\theta / y)$, and we define $\hat{g}_S = 1/S \sum_{s=1}^{S} g(\theta^{(s)})$, then $\hat{g}_S$ converges to $E[g(\theta) / y]$ when $S \Rightarrow \infty$. This function tells us in practical terms that we can approximate $E[g(\theta)/y]$ simply by taking averages of the function of interest evaluated in the random sample. Additionally, confidence intervals of 95% or 99% can be calculated based on the posterior density.

In general, simulation techniques based on Markov chains (MCMC) are the most commonly used due to their generality and flexibility, and among these the most common is the Metropolis-Hastings algorithm (see Ntzoufras (2009) for further details). It is necessary to make clear some of the terminology related to these types of simulators. In the first place, these methods must converge to a stationary distribution. It is often not clear how many times should the algorithm iterate, which is why several diagnostic tests must be visualized and observed in order to monitor the algorithm. A second definition are the so called iterations. They refer to a cycle during which the algorithm has generated a complete set of parameters arising from the posterior distribution. In the previous notation, for example, $\theta^{(5)}$ refers to the $\theta$ vector generated in the fifth iteration. After this, we must know how many iterations will be carried out. Additionally, a set of initial values that can be denoted as $\theta^{(0)}$ is necessary. On the other hand, a number of iterations must be eliminated with the purpose of avoiding the influence of initial values. Finally, since the final MCMC is not independent, the degree of autocorrelation of the generated values must be monitored. In order to avoid this inconvenient, the iterations of a given number of lags are utilized. For example, if three lags are used, this means that only the observations 1, 4, 7, etc. are used. In the result of the MCMC, the so called Monte Carlo error must be observed, which means the variability of each estimate due to simulation. It is obvious that that error must be low with the aim of calculating the relevant parameters with precision.

In our case, we have 12 probabilities in vector $\theta$. Since we are dealing with probabilities, we use as a priori distribution uniform distributions for each parameter. We take lags of 10 and eliminate the first 1,000 iterations, which leaves us with a total of 1,900 iterations.

3.1.3. *The data*

The ENAHO 2007-2010 panel sample was utilized. In this sample, 6213 individuals that were interviewed on four occasions were identified; that is, during the whole four years that make up this panel. Besides, they were required to have complete information in the variables used in this study, that is, condition of activity regarding working age population, sex, area of residence, and age. Since each of these individuals were observed in four occasions, then three mobility processes can be identified: 2007 to 2008, 2008 to 2009, and 2009 to 2010. Between each of these processes there are 12 months. Four versions of the N matrices are reported in the annex: one for each transition between 2 contiguous years and the fourth for the set of three mobility processes.

### 3.2 Results of the transition analysis

Charts 2 and 3 show the results of matrices Q and P, respectively, for the set of labor mobility processes between 2007 and 2010. Note that, as reported in Chart 2, in any of the two periods, approximately 75% of the working age population was occupied, little more than 20% was inactive, and unemployment, in any of its forms, was very low —both definitions combined were around 4%. On the other hand, Chart 3 shows, as expected, that most of the occupied were still in the same state 12 months later. An important part of the inactive ones present a similar behavior, but in a lesser degree in comparison with the occupied. Most part of the non-occupied, however, in any of their two forms, tend to show a different state 12 months later.

**Chart 2**

**Peru 2007-2010: Relative distribution of persons w.r.t. the total general according to condition of labor activity (matrix Q).**

| | | Final period | | | |
|---|---|---|---|---|---|
| | | Occupied | Active unempl. | Hidden unempl. | Inactive |
| Initial period | Occupied | 65.8 | 1.0 | 0.8 | 6.9 |
| | Active unempl. | 1.2 | 0.3 | 0.1 | 0.7 |
| | Hidden unempl. | 0.9 | 0.1 | 0.2 | 0.9 |
| | Inactive | 7.0 | 0.7 | 0.8 | 12.5 |

**Source:** ENAHO panel 2007-2010. Authors' preparation.

**Chart 3**

| Peru 2007-2010: Transition matrix for persons according to their labor activity condition (matrix P) | | | | | |
|---|---|---|---|---|---|
| | | **Final period** | | | |
| | | **Occupied** | **Active unempl.** | **Hidden unempl.** | **Inactive** |
| **Initial period** | **Occupied** | 88.3 | 1.3 | 1.1 | 9.3 |
| | **Active unempl.** | 50.8 | 14.4 | 5.9 | 28.8 |
| | **Hidden unempl.** | 43.3 | 5.0 | 9.6 | 42.1 |
| | **Inactive** | 33.5 | 3.4 | 3.7 | 59.4 |

**Source:** ENAHO panel 2007-2010. Authors' preparation.

One aspect that raises attention (and was mentioned in earlier works) is that transitions are more frequent between occupation and inactivity than between these states and unemployment. Thus, for example, as in Chart 3, it is observed that from the total of occupied persons in the initial period, 9% report as inactive in the final period, whereas little more than 2% is reported as unemployed in any of its forms. On the other hand, from the total of inactive in the initial period, 34% are occupied in the final period and only around 8% in some of the types of unemployment.

Nevertheless, the results of transitions reported in Chart 3 may not be very reliable, either due to lack of precision, or because they are not statistically significant. Regarding this concern, we utilize methods of Bayesian estimation so as to calculate some statistics and submit them to hypothesis tests. In Chart 4, the mean, the median and the upper and lower limits for a confidence interval for each element of matrix *P* are reported, among others. Bayesian estimation techniques were used to this effect, which allow an evaluation of certain features of these probabilities. In all cases we can reject that the transition probabilities are null with 5% confidence. It is true, however, that some probabilities (especially those of states with low population such as both forms of unemployment) have relatively wide confidence intervals.

**Chart 4**

**Peru 2007-2010: Results of some statistics of the transition probability distribution using Bayesian estimation methods[1]**

| | Standard deviation | MC_error | Mean | Median | IC: lower limit | IC: upper limit |
|---|---|---|---|---|---|---|
| **p11** | 0.0027320 | 5.77E-05 | 0.88300 | 0.88300 | 0.87760 | 0.88820 |
| **p12** | 0.0009551 | 2.33E-05 | 0.01289 | 0.01285 | 0.01115 | 0.01487 |
| **p13** | 0.0008953 | 1.76E-05 | 0.01098 | 0.01097 | 0.00932 | 0.01281 |
| **p14** | 0.0024950 | 5.23E-05 | 0.09317 | 0.09324 | 0.08838 | 0.09794 |
| **p21** | 0.0231800 | 5.70E-04 | 0.50650 | 0.50770 | 0.46030 | 0.55010 |
| **p22** | 0.0167000 | 3.73E-04 | 0.14540 | 0.14450 | 0.11400 | 0.18040 |
| **p23** | 0.0114200 | 2.23E-04 | 0.06006 | 0.05911 | 0.03924 | 0.08411 |
| **p24** | 0.0218900 | 5.05E-04 | 0.28810 | 0.28750 | 0.24810 | 0.33290 |
| **p31** | 0.0238200 | 6.23E-04 | 0.43150 | 0.43170 | 0.38440 | 0.47710 |
| **p32** | 0.0111200 | 2.16E-04 | 0.05054 | 0.04973 | 0.03131 | 0.07428 |
| **p33** | 0.0142600 | 3.28E-04 | 0.09795 | 0.09740 | 0.07156 | 0.12760 |
| **p34** | 0.0244700 | 6.57E-04 | 0.42000 | 0.42010 | 0.37430 | 0.47130 |
| **p41** | 0.0076720 | 1.81E-04 | 0.33500 | 0.33490 | 0.32030 | 0.34990 |
| **p42** | 0.0028750 | 6.93E-05 | 0.03413 | 0.03408 | 0.02884 | 0.03977 |
| **p43** | 0.0030290 | 7.92E-05 | 0.03685 | 0.03677 | 0.03112 | 0.04294 |
| **p44** | 0.0080250 | 2.23E-04 | 0.59400 | 0.59410 | 0.57810 | 0.60920 |

**Notes**

[1] WinBugs was utilized, the first 1,000 estimations were discarded, and the size of the effective sample was 1,900.

**Source:** ENAHO panel 2007-2010. Authors' preparation.

The total, structural and circular labor mobility indices, which are obtained from the ***Q*** matrix, are reported in Chart 5. Total mobility, meaning the proportion of the population that switched states, measured with the indicator ***T***, is 21% for the set of labor transitions between 2007 and 2010. The stratification of the population by gender, age and area of residence shows that among the younger cohorts, women, and urban area residents, mobility is higher (see Graph 1). The larger portion of mobility arises from "interchange" of positions, or circular mobility[12]. Structural mobility is approximately 1%. This important participation of circular mobility explains the fact that the population distribution in the four states is very similar in the initial and final periods.

[12] The further decomposition of total mobility in circular and structural according to gender, age and area confirms that most part of labor mobility is circular.

**Chart 5**
**Peru 2007-2010: Total, circular and structural labor mobility indices**

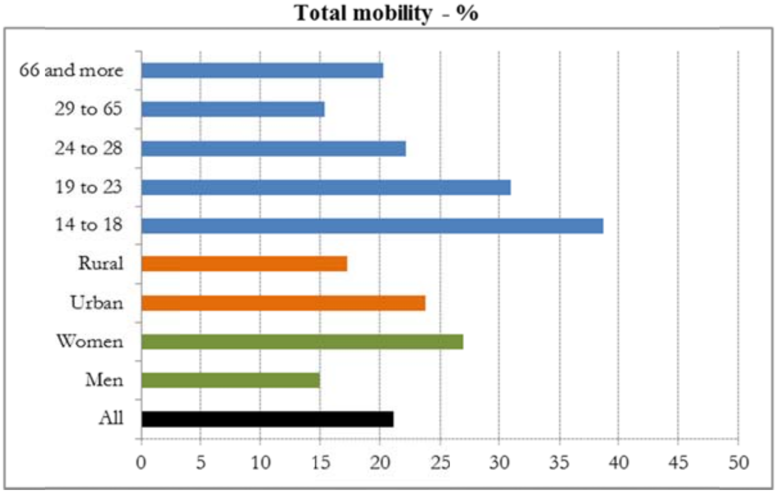
| | 2007-2010[1] | 2007-2008[2] | 2008-2009[2] | 2009-2010[2] |
|---|---|---|---|---|
| **Total - T** | 21.2 | 21.8 | 20.8 | 20.9 |
| **Circular - C** | 20.7 | 20.7 | 19.3 | 20.3 |
| **Structural - S** | 0.4 | 1.1 | 1.5 | 0.6 |

**Notas:**

[1] Column 2007-2010 was calculated taking into consideration the 3 transitions in that period, that is, these results are an average of the three transitions. In the other cases, only the transitions of 2 contiguous years are considered.

**Source**: ENAHO panel 2007-2010. Authors' preparation.

**Graph 1**
**Peru 2007-2010: Total mobility according to age, gender and area of residence**
**Total mobility - %**




What is the destination of the persons that switched states? In how much time is a person expected to change its initial state? In order to find answers to these questions we use the information of matrix ***P*** as reported in Chart 3, whose statistical features are in Chart 4.

The results of the destination state given a switch and the expected time for a state switch are reported in Chart 6. It can be noted that: (i) the destination state of the occupied that switch state is in a majority of cases inactivity (80%), (ii) in a similar way, the destination of most of inactive that switch states is occupation (83%), (iii) most of the active unemployed transit into occupation (59%), whereas the hidden unemployed have almost the same chance of becoming occupied (48%) than becoming inactive (47%). It should be highlighted that there is much more mobility between occupation and inactivity than between the former and unemployment in any of its variants. This result should not surprise since the volume of unemployment in any of the two reported variants is low, in both absolute and relative terms.

**Chart 6**
**Peru 2007-2010: Labor mobility indices - probabilities of switching states and number of years until initial state is abandoned**

| Initial state | Final state | | | | Years until switching state |
|---|---|---|---|---|---|
| | Occupied | Active unemp. | Hidden unemp. | Inactive | |
| **Occupied** | n.a. | 11.0 | 9.4 | 79.6 | 8.6 |
| **Active unemp.** | 59.4 | n.a. | 7.0 | 33.7 | 1.2 |
| **Hidden unemp.** | 47.9 | 5.6 | n.a. | 46.5 | 1.1 |
| **Inactive** | 82.6 | 8.4 | 9.1 | n.a. | 2.5 |

**Source:** ENAHO panel 2007-2010. Authors' preparation.

In Chart 6 the number of years that pass in average until a person abandons a state is also reported. In the case of the occupied, it is almost nine years, whereas any type of unemployment lasts little more than a year. Inactivity, on the other hand, can last between two and three years before switching states. The transition from each initial state to the other ones is approximated with the probability distribution mentioned earlier. That is, read as a whole, in the case of the occupied, they take almost nine years in leaving that state, and the most likely state towards which they transition is inactivity. On the other hand, the inactive remain as such for approximately 2.5 years, and the most likely state towards which they switch is being occupied.

## 4. DETERMINANTS OF CHANGES IN THE OCCUPATIONAL SITUATION: REGRESSION ANALYSIS.

### 4.1. Methodology

The labor situation of any working age person at a given point in time arises from the confluence of a number of factors that determine, on the one hand, the decision of this person to work, and on the other hand, that the opportunity to do so exists. If at the labor market all the jobs were salaried, evidently all the work opportunities would be provided by firms that create jobs. But if not all jobs are salaried and self-employment exists, the working opportunities will also result from the creation or identification of alternatives to generate income under production modes that do not require salaried work (self-employment). In any case, to observe a person at work – be it under a salary or as self-employed – is the result of the interaction of factors that determine supply and demand (or self-generation) of employment.

In consequence, we will assume that the labor situation (working or not working) of a person depends on variables that determine his decision to work and of variables that take into account the behavior of labor demand. As usual in the literature, we have considered that the decision to work depends on human capital, socio-demographic attributes of the person and the family it belongs to, and of family income. Specifically, age and years of schooling have been considered as proxies for human capital; civil status, the condition as head of the household, and the composition of the household according to members' age groups as proxies for socio-demographic features; and family income, excluding the labor income of the person whose labor situation is being modeled, as a proxy for the reserve income.

The variables that have been taken into consideration from the demand side are the following: size of the establishment and size of the economic sector; in both cases the size has been approximated by the number of workers. Other variables that are not exclusively attributes of supply or demand and have been included are the area of residence (urban or rural), and the occupational category. As will be shown below, thanks to the use of panel samples, the differences of some variables were utilized.

We employed logit regressions for the analysis of the determinants of the transition from occupation into non-occupation that includes the other three states (e.g. open or hidden non-occupation and inactivity). Note that the logit is being used for whether an individual switches states or not in two moments of time. Then, if $y_i$ is the variable that measures the result of the transition, and $e_{i,t}$ is the state of person *i* in period $t$, then:

$$y_i = 1 \quad if \quad e_{i,t+1} = e_{i,t} = occupied$$

and

$$y_i = 0 \quad if \quad e_{i,t+1} \neq e_{i,t} = occupied$$

The probability that an individual *i* is observed as occupied in $t$ as well as in $t + 1$, that is, that $y_i = 1$, given the set of characteristics of this individual collected in vector $\boldsymbol{x}_i$, is the following:

$$P(y_i = 1 \mid \boldsymbol{x}_i) = \frac{\exp(\boldsymbol{x}_i'\beta)}{1 + \exp(\boldsymbol{x}_i'\beta)}.$$

Although the estimated coefficients of β are the ones that determine the behavior of probabilities, their more intuitive interpretation is less clear. In that case, the odds-ratio are resorted to in order to show not only in which direction they affect the probability of being occupied in both periods, but also their relative importance over the probability. Consider the following ratio[13]:

$$\Omega(\boldsymbol{x}) = \frac{P(y = 1 \mid \boldsymbol{x})}{P(y = 0 \mid \boldsymbol{x})} = \frac{P(y = 1 \mid \boldsymbol{x})}{1 - P(y = 1 \mid \boldsymbol{x})}.$$

It can be shown that the change in one unit in variable $x_k$, keeping the rest of the variables constant, modifies the ratio of probabilities between one and other result in a certain positive factor equal to:

$$\frac{\Omega(\boldsymbol{x}, x_k + 1)}{\Omega(\boldsymbol{x}, x_k)} = \exp(\beta_k) = n_k.$$

Where $n_k > 1$ means that the probability of $P(y = 1 \mid \boldsymbol{x})$ with respect to $P(y = 0 \mid \boldsymbol{x})$ when $x_k$ increases in one unit. If, on the contrary, $n_k < 1$, then the ratio of those probabilities diminishes[14].

13 See in chapter 4 of Long and Freese (2006) a very clear presentation on odds-ratios and, in general, on binary logit models.

14 It is important to point out that the value taken by $n_k$ is independent of the values that the other variables take.

*The data*

The utilized information comes from the panel sample of the National Household Survey (ENAHO) of the period 2007 to 2010[15]. From this panel sample, and in contrast to what is done with cross-sample data, what was modeled here is the change in the labor situation. In the first part of this piece it was shown that, taking into account four states of the working age population (e.g. occupied, active non-occupied, hidden non-occupied and inactive), the most frequent changes in state are between occupation and inactivity, and vice versa. What is modeled at present is whether there was a switch of states or not, having occupation as an initial state (e.g. occupied in 2007). The switch of state is modeled in a dichotomy fashion, where staying occupied is "1" and ceasing to be occupied is "0" (i.e. both types of unemployment and inactive in 2008). In chart 7, the distribution of the sample is provided, separating between men and women.

**Chart 7**

**Peru 2007-2008: Distribution of the panels sample of occupied men and women in 2007 according to labor status[1] in 2008.**

| Labor status | Men | | Women | |
|---|---|---|---|---|
| | Obs. | % | Obs. | % |
| Occupied | 2,023 | 93.7 | 1,613 | 84.3 |
| Unemployed | | | | |
| Open unemployment | 30 | 1.4 | 20 | 1.0 |
| Hidden unemployment | 17 | 0.8 | 34 | 1.8 |
| Out of EAP | 88 | 4.1 | 247 | 12.9 |
| Sub-total unemployed | 135 | 6.3 | 301 | 15.7 |
| Total | 2,158 | 100.0 | 1,914 | 100.0 |

**Notes**

1 Labor categories are defined by INEI. The identifying variable is in the same database provided by INEI.

**Source:** ENAHO Panel 2007-2010. Authors' preparation.

15 The panel actually covers the period 2007 – 2011. However, at the time of making the econometric exercises, only data until 2010 was available. In this work, only the results of the 2007-2008 panel are presented. The results of other panels can be requested to the authors. The original databases can be downloaded from http://www.inei.gob.pe/srienaho/Consulta_por_Encuesta.asp.

All the explanatory variables were calculated for 2007 (starting year) when people were occupied. Beside the variables in levels, the variations in household income and in sectoral employment were included. It is important to note that in the panel sample that was used, the same individuals are observed with an interval of 12 months between observations[16].

### 4.2 The results

In Chart 8 the results of the logit regressions are reported separately for men and women between 18 and 70 years. The corresponding coefficients and p-values are provided.

The higher the age, the higher the probability that a person stays occupied, in both men and women. This relation is concave throughout all ages here considered (i.e. 18 to 70 years) and increasing both for men and women, respectively[17]. Its effect on the probability of being occupied in both years with respect to ceasing to be is very large, as can be appreciated in the odd ratio: one additional year of age causes that the probability of staying at work is 1.24 and 1.15 times higher for men and women, respectively, keeping the other variables constant. Years of schooling, in contrast, have a negative effect on the same probability. The relation is convex and negative for almost the whole range in which schooling years vary (from 0 to 18 years, in both cases).

---

16 Surveys do not provide information on what happened within those 12 months, nor when the switch of state occurred.

17 We say increasing in spite of being concave, because the maximum is reached at 83 and 91 years for men and women, respectively. These ages are above the range of age considered here.

**Chart 8**

**Results of logit regressions on mobility from occupied status[1].**
**Peru 2007-2008: Men and women between 18 and 70 years.**

| Variables and description | Men Coefficient (p-value) | Men Odd ratio[2] | Women Coefficient (p-value) | Women Odd ratio[2] |
|---|---|---|---|---|
| Age (years) | 0 (0.00) | 1.237 | 0.145 (0.00) | 1.156 |
| Squared age | -0.003 (0.00) | 0.997 | -0.002 (0.00) | 0.998 |
| Schooling years | -0.317 (0.01) | 0.728 | -0.083 (0.10) | 0.921 |
| Schooling years squared | 0.017 (0.00) | 1.018 | 0.005 (0.09) | 1.005 |
| Head of household (dummy = 1) | 0.29 (0.40) | 1.337 | -0.062 (0.80) | 0.940 |
| Married or live-in partner (dummy = 1) | 0.575 (0.045) | 1.778 | -0.279 (0.13) | 0.757 |
| Occupational category (omitted: self-employed) | | | | |
| Employer | 0.523 (0.25) | 1.687 | 0.579 (0.23) | 1.784 |
| Salaried | 0.351 (0.14) | 1.420 | -0.205 (0.30) | 0.814 |
| Other categories | -0.998 (0.00) | 0.369 | -0.344 (0.06) | 0.709 |
| Size of establishment (# of workers) | 0 (0.19) | 1.000 | 0 (0.00) | 1.000 |
| Number of household members according to age | | | | |
| Up to 2 years | 0.121 (0.13) | 1.128 | -0.071 (0.13) | 0.932 |
| 3 to 5 years | 0.102 (0.68) | 1.108 | -0.205 (0.12) | 0.815 |
| 6 to 10 years | -0.061 (0.73) | 0.941 | -0.067 (0.51) | 0.935 |
| 11 to 17 years | 0.068 (0.58) | 1.071 | -0.02 (0.81) | 0.980 |
| Family income less labor income (per capita, 2007, logarithms) | -0.307 (0.02) | 0.736 | -0.319 (0.00) | 0.727 |
| Ratio of family income in 2007 w.r.t. 2008 (logarithms) | 0.689 (0.00) | 1.992 | 0.345 (0.00) | 1.412 |
| Volume of employment by activity sectors (2007, logarithms) | 0.385 (0.01) | 1.470 | 0.19 (0.06) | 1.209 |
| Ratio of volume of employment in 2007 w.r.t. 2008 (logarithms) | -4,623 (0.14) | 0.010 | -1,932 (0.26) | 0.145 |
| Residence in urban areas (omitted = rural) | -0.557 (0.03) | 0.573 | -0.161 (0.37) | 0.851 |
| Constant | -3,408 (0.18) | | -1 (0.71) | |
| Number of observations | 2,158 | | 1,914 | |
| Pseudo $R^2$ | 0.1714 | | 0.051 | |

**Notes:**

[1] The dependent variable takes a value of 1 when the individual was occupied in both years and a value of 0 when he/she stops being occupied in the second year.

[2] To stay occupied vs. ceasing to be occupied.

**Source:** ENAHO Panel 2007-2008. Authors' preparation.

It is curious that, as both variables are proxies for human capital, the signs of the coefficients are opposite. One possible explanation could be as follows. If age is considered as a proxy for experience at work, and thus, learning on the job, then the higher the age, the more experience a worker has. And in consequence, the higher amount of skills, which make employing this person worthwhile. Schooling, on the other hand, is higher among the youngest people who, because of that, have less experience. Thus, it is possible that the schooling variable is capturing part of the aforementioned association (younger, less age, lower probability of staying at work).

To be the head of a household does not contribute in a significant way in any of both sexes, and the marriage status only contributes in the case of men. Married and live-in partners have a higher probability of being occupied in both periods, by an amount of 1.78 times.

Regarding the occupational category at the initial moment, only the category "other" is significant, which includes mainly non-paid family workers (NPFW from now on) and domestic workers. This is valid for both sexes. These workers, in comparison to the self-employed, have a lower probability of being occupied in both periods. This result is to be expected in so far as the NPFW tend to be young, they usually work part-time, and many of them still combine working periods with educational activities (especially in urban areas).

In the case of employers and salaried workers, the coefficients are not statistically significant, and thus, it is not expected that their probability of staying occupied in both periods is different than that of the self-employed. The size of the establishment, approximated by the number of workers, is not statistically significant.

The composition of the family to which a person belongs, approximated by the number of persons of different age cohorts, is not a statistically significant dimension, even for women. This result is surprising, since one would expect that in the case of women the presence of children would discourage work, especially when they are very young or in pre-school age.

Family income per capita, discounted by the person's labor income, is statistically significant and contributes negatively to the probability of being occupied in both periods. If this income is considered a proxy of wealth, and this one of the determinants of the reserve labor income, then it is expected that the higher the income the lower the probability of being occupied (see, for example, Bloemen and Stancanelli 2001, and Algan et al. 2002). The change in this income between 2007 and 2008, measured as the ratio of the first by the second, indicates that a drop in income in 2008 with respect to 2007 increases the probability of staying occupied, which reinforces the idea that the probability of staying occupied is affected through the reserve salary.

The size of the sector of activity, measured by the volume of employment in 2007 in each of the 17 sectors under consideration, contributes significantly and positively in the probability of being occupied in both years. This variable would be capturing the changes in aggregate demand for labor in the large sectors of economic activity. As expected, the higher the volume of employment and its growth rate, the higher the probability of staying occupied. However, the changes in employment volume between 2007 and 2008 are not statistically significant even though the sign is as expected. Finally, the probability of staying occupied is higher in rural areas than in urban, but only among men. Here the status of being rural seems to capture the fact that in this type of areas, domestic forms of production predominate (i.e. family production units), where there is not much creation or destruction of jobs. This is in contrast to urban areas where salaried forms of employment are more common.

## 5. CONCLUSIONS

The descriptive part of this document has allowed the identification of the existence of an important degree of labor mobility in Peru. On average, taking into consideration 3 transitions every 12 months between 2007 and 2010 on a national scale, 21% of the working age population switches between the 4 possible considered states; that is, occupied, active unemployment, hidden unemployment, and inactive. The larger part of this mobility is circular, which means that during these 4 years there hasn't been a significant change in the distribution of the population in these 4 states. Another finding was also that mobility is higher in urban areas with respect to rural areas, and is also higher among women than among men. According to age groups, the degree of mobility is 2 times higher among the youngest in comparison to the age group of 29 to 65 years (in this later group are the highest rates of labor participation).

In terms of destinations of the transitions, taking into consideration only those who switch states, of those that were occupied in the starting year and no longer are in the final year, 80% are inactive. The remaining 20% is distributed more or less equally between two types of unemployment. Coincidentally, among those that were inactive in the starting year and aren't in the final, 83% are occupied. This result, which has already been found in other studies for Peru, suggests that unemployment is not an intermediate state in the transition between being occupied and non-occupied, in any of both directions. That is, neither at the loss of occupation nor at the return to it. It may be the case that, since 12 months elapse between the initial and the final event, and since unemployment is of short duration – as previous works suggest -, the lack of a stronger link between occupation and unemployment is precisely due to the fact that the interval of time between observations is very long. Nevertheless, it is important to note that in previous studies with panels with 3 months between observations, a similar result was found; see Chacaltana (2001).

The transition matrices also allow one to estimate the expected time that must elapse until the initial state is changed. The results show that the occupied persons will remain as such for 8.6 years, the unemployed in any of its modalities slightly more than one year, and the inactive 1.1-1.2 years. The duration of unemployment obtained here is not consistent with previous estimations that indicate periods of at most 13.5 weeks (i.e. 0.25 years; see Díaz and Maruyama 2000). Once more, the size of the time interval between two interviews may be biasing this last result. More studies on this particular aspect are necessary, but that would require information that is not currently being generated in Peru[18].

Regarding the analyses of potential determinants of transitions from occupation to non-occupation, in which the latter includes any of the other 3 states (i.e. unemployment in its two forms and inactivity), one can conclude that the stock of human capital matters. The curious thing is that both variables of human capital (i.e. age and schooling) affect the probability of staying occupied in opposite directions: more experience increases the probability of staying occupied, whereas more years of schooling reduce this probability. The explanation we attempt for this result is that, while there is a negative correlation (as a proxy for work experience) and years of schooling, the effect of age is dominating even the years of schooling (which should contribute positively to the probability of staying occupied). This is so, because the youngest persons present the highest levels of schooling and at the same time the highest indices of mobility.

Household income per capita (excluding the individual's) reduces the probability of staying occupied. If we take this income as a proxy for wealth, this is a result that is to be expected in so far as it is a determinant of the reservation wage. This result is reinforced if one takes also the change in income between periods into consideration: a drop in income increases the probability of staying occupied.

[18] For example, representative panel samples of the population every 3 months have been discontinued for more than a decade, and were made only for some years. Currently, only panels every 12 months are available.

Regarding the variables of labor demand, the levels of employment and their increases contribute to augment the probability of staying occupied. In order to find this result, a classification of employment in 17 sectors of economic activity was utilized, but only the variable in levels was statistically significant. The idea underlying the inclusion of changes in the levels of employment is that these could represent shocks in the labor markets. Econometric results yield the correct sign, but not at statistically significant levels. This could be due to the fact that in the period under consideration (i.e. transitions between 2007 and 2008) there weren't changes in employment levels large enough to have significant impacts on the probability of keeping one's job. This is an area that merits further investigation.

Is the high labor mobility found in the Peruvian case a problem? Not necessarily, if one takes into consideration that the most part, if not the total, of mobility is circular. This means that the distribution between the considered states is not showing that, for example, the proportion of working age population that is occupied is getting smaller. From this perspective, it may be a source of concern that among the youngest people (up to 18 years) there is structural mobility, and this is associated to an increase in the proportion of occupied and concomitantly a reduction in the inactive. If this is happening at the cost of, for example, the process of acquisition of formal education, then that could indeed be a subject to consider in the policy discussion.

In this line of discussion, in general terms, the high importance of transitions between occupation and inactivity, and vice versa, in a context of economic growth and employment growth, suggests that these transitions are mainly undergone by the secondary labor supply in the families. We have shown that among the youngest and women, the indices of mobility are higher in comparison to those of men and middle-aged people (which concentrate the prime-age workers from the labor point of view).

## References

Algan, Y., A. Chéron, J. Hairault and F. Langot (2003). Wealth effect on labor market transitions. *Review of Economic Dynamic*, 6(2003), pp. 156-178.

Bloemen, H. and E.G.F. Stancanelli (2001). Individual wealth, reservation wages, and transitions into employment. *Journal of Labor Economics*, 21(2), pp. 400-439.

Bosch, M and W. Maloney (2010). Comparative analysis of labor market dynamics using Markov processes: an application to informality*. Labour Economics* 17(2010), pp. 621-631.

Bosch, M and W. Maloney (2005). Labor market dynamics in developing countries: comparative analysis using continuous time Markov processes. *World Bank Policy Research Working Paper* 3583.

Chacaltana, J. (2001). Dinámica del desempleo. In INEI (editor). *¿Qué sabemos sobre el desempleo en el Perú? Familia, trabajo y dinámica ocupacional. Análisis de la Encuesta Nacional de Hogares*. Lima: INEI, 7-43.

Contreras, D., L. de Mello and E. Puentes (2010). The determinants of labour force participation and employment in Chile. *Applied Economics.* Londres, 43(21), pp. 2765-2776.

Da Silva, A. and V. Pero (2009). Segmentação do mercado de trabalho e mobilidade de renda entre 2002 e 2007. Working paper presented in en ANPEC 2008. http://www.anpec.org.br/encontro2008/artigos/200807211027150-.pdf

Díaz, J. J. and E. Maruyama (2000). La dinámica del desempleo urbano en el Perú: tiempo de búsqueda y rotación laboral. Final report.

Garavito, C. (2010). Vulnerabilidad en el empleo, género y etnicidad en el Perú. *Economía*. Lima, vol. 33, num. 66, pp. 89-127.

García, M. and A. Naudon (2012). Dinámica laboral en Chile. *Documentos de Trabajo* 659. Santiago de Chile: Banco Central de Chile.

Herrera, J. and N. Hidalgo (2002). Vulnerabilidad del empleo en Lima: un enfoque a partir de encuestas a hogares. *Boletín del Instituto Francés de Estudios Andinos* 31, número 3. Lima: Instituto Francés de Estudios Andinos, pp: 553-597.

Herrera, J. and G. D. Rosas Shady (2003). Labor market transitions in Peru. *Document de Travail* DT/2003/14. Paris: DIAL.

Long, J. S. and J. Freese (2006). Regression models for categorical dependent variables using Stata. Texas: Stata Press.

Morales, R., J. Rodríguez, M. Higa and R. Montes (2010). Transiciones laborales, reformas estructurales y vulnerabilidad laboral en el Perú: 1998-2008. In Rodríguez J. and A. Berry (ed.). *Desafíos laborales en América Latina después de dos décadas de reformas estructurales. Bolivia, Paraguay y Perú 1997-2008*. Lima: Instituto de Estudios Peruanos and Fondo Editorial de la Pontificia Universidad Católica del Perú., pp. 47-116.

Ntzoufras, L. (2009). *Bayesian Modeling using WinBugs*. New Jersey: John Wiley & Sons.

Pessino, C. and L. Andrés (2000). La dinámica laboral en el Gran Buenos Aires y sus implicaciones para la política laboral y social. Documento de Trabajo 173. Buenos Aires: CEMA. http://cdi.mecon.gov.ar/biblio/doc/cema/doctrab/173.pdf

Programa de Estadísticas y Estudios Laborales (1998). La dinámica del desempleo abierto en el Perú. *Boletín de Economía Laboral* 9, año 3. Lima: Ministerio de Trabajo y Promoción del Empleo, pp. 2-10.

Programa de Estadísticas y Estudios Laborales (1996). Duración y determinantes del desempleo urbano en el Perú. *Boletín de Economía Laboral* 1, año 1. Lima: Ministerio de Trabajo y Promoción del Empleo, pp. 7-14.

Saavedra, J. C. and J. Luque (2008). Relación entre la rotación de la mano de obra, subcobertura frente al riesgo de desempleo e ingresos laborales. Una primera aproximación. In Velazco, T., H. Ñopo and J. Rodríguez (editores). *Segunda Conferencia de Economía laboral. Tendencias del empleo, capital humano, informalidad y rotación laboral*. Lima: Ministerio de Trabajo y Promoción del Empleo.

Rodríguez, J. and Minoru Higa (2010). Informalidad, empleo y productividad. In Rodríguez J. and A. Berry (editores). *Desafíos laborales en América Latina después de dos décadas de reformas estructurales. Bolivia, Paraguay y Perú 1997-2008*. Lima: Instituto de Estudios Peruanos and Fondo Editorial de la Pontificia Universidad católica del Perú, pp. 117-182.

Sedlacek, G., R. Paes de Barros and S. Varandas (1990). Segmentacao e mobilidade no mercado de trabalho: a carteira de trabalho em Sao Paulo. *Pesquisa e Planejamento Economico*, 20(1), pp. 87-104.

Zipkin, E., C. C. Jenelle and E. Cooch (2010). A primer on the application of Markov chains to the study of wildlife disease dynamics. *Methods in Ecology and Evolution*, 2010(1), pp. 92-98.

**ÚLTIMAS PUBLICACIONES DE LOS PROFESORES**
**DEL DEPARTAMENTO DE ECONOMÍA**

*Libros*

Felix Jiménez
2012 *Crecimiento económico: enfoques y modelos.* Lima, Fondo Editorial, Pontificia Universidad Católica del Perú.

Janina León Castillo y Javier M. Iguiñiz Echeverría (Eds.)
2011 *Desigualdad distributiva en el Perú: Dimensiones.* Lima, Fondo Editorial, Pontificia Universidad Católica del Perú.

Alan Fairlie
2010 Biocomercio en el Perú: Experiencias y propuestas. Lima, Escuela de Posgrado, Maestría en Biocomercio y Desarrollo Sostenible, PUCP; IDEA, PUCP; y, LATN.

José Rodríguez y Albert Berry (Eds.)
2010 *Desafíos laborales en América Latina después de dos décadas de reformas estructurales. Bolivia, Paraguay, Perú (1997-2008).* Lima, Fondo Editorial, Pontificia Universidad Católica del Perú e Instituto de Estudios Peruanos.

José Rodríguez y Mario Tello (Eds.)
2010 *Opciones de política económica en el Perú 2011-2015.* Lima, Fondo Editorial, Pontificia Universidad Católica del Perú.

Felix Jiménez
2010 *La economía peruana del último medio siglo.* Lima, Fondo Editorial, Pontificia Universidad Católica del Perú.

Felix Jiménez (Ed.)
2010 *Teoría económica y Desarrollo Social: Exclusión, Desigualdad y Democracia. Homenaje a Adolfo Figueroa.* Lima, Fondo Editorial, Pontificia Universidad Católica del Perú.

José Rodriguez y Silvana Vargas
2009 *Trabajo infantil en el Perú. Magnitud y perfiles vulnerables. Informe Nacional 2007-2008.* Programa Internacional para la Erradicación del Trabajo Infantil (IPEC). Organización Internacional del Trabajo.

Óscar Dancourt y Félix Jiménez (Ed.)
2009 *Crisis internacional. Impactos y respuestas de política económica en el Perú*. Lima, Fondo Editorial, Pontificia Universidad Católica del Perú.

*Serie: Documentos de Trabajo*

No. 333 "Los programas de garantía de rentas en España: la renta mínima de inserción catalana y sus componentes de inserción laboral". Ramón Ballester

No. 332 "Real Output Costs of Financial Crises: a Loss Distribution Approach". Daniel Kapp y Marco Vega. Junio, 2012.

No. 331 "Microeconomía: aplicaciones de la teoría del consumidor". Cecilia Garavito. Junio, 2012.

No. 330 "Desprotección en la tercera edad: ¿estamos preparados para enfrentar el envejecimiento de la población?". Luis García Núñez. Junio, 2012.

No. 329 "Microeconomía: preferencias y elecciones de los consumidores". Cecilia Garavito. Mayo, 2012.

No. 328 "Orígenes históricos de la desigualdad en el Perú". Carlos Contreras, Stephan Gruber y Cristina Mazzeo. Mayo, 2012.

No. 327 "Residual Based Test for Cointegration with GLS Detrented Data". Pierre Perron y Gabriel Rodríguez. Marzo, 2012

No. 326 "Cuál es el costo de la contaminación ambiental minera sobre los recursos hídricos en el Perú?: Comentarios". Alfredo Dammert, Arturo Vásquez, Raúl García, Víctor Zurita, Humberto Ortiz y Erix Ruiz. Noviembre, 2011.

No. 325 "Some Stylized Facts of Returns in the Foreign Exchange and Stock Markets in Peru". Alberto Humala y Gabriel Rodríguez. Setiembre, 2011.

No. 324 ¿Barreras lingüísticas en la educación? La influencia de la lengua materna en la deserción escolar. Efraín Rodríguez Lozano. Agosto, 2011.

Departamento de Economía - Pontificia Universidad Católica del Perú
Av. Universitaria 1801, Lima 32 – Perú.
Telf. 626-2000 anexos 4950 - 4951
http://www.pucp.edu.pe/economia