EARNINGS DYNAMICS AND INEQUALITY IN VENEZUELA: 1995-1997

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ABSTRACT

In this paper, we decompose the variance of logarithmic monthly earnings of prime age males into its permanent and transitory components, using a five-wave rotating panel from the Venezuelan "Encuesta de Hogares por Muestreo" from 1995 to 1997. As far as we know, this is the first time a variance components model is estimated for a developing country. We test several specifications and find that an error component model with individual random effects and first order serially correlated errors fits the data well. In the simplest model, around 22% of earnings variance is explained by the variance of permanent component, 77% by purely stochastic variation and the remaining 1% by serial correlation. These results contrast with studies from industrial countries where the permanent component is predominant. The permanent component is usually interpreted as the results of productivity characteristics of individuals whereas the transitory component is due to stochastic perturbations such as job and/or price instability, among others. Our findings may be due to the timing of the panel when occurred precisely during macroeconomic turmoil resulting from a severe financial crisis. The findings suggest that earnings instability is an important source of inequality in a region characterized by high inequality and macroeconomic instability.

Keywords: Components of Variance Models, Earnings Inequality, Earnings Dynamics, Latin America

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1. Introduction

The study of earnings dynamics has become a special matter of interest in developed countries due to the rise in inequality that has been documented for some leading industrial economies.[1] This is because the study of earnings dynamics allows researchers to understand how much earnings vary over time and to elucidate if an individual's position in the earnings distribution is temporary or more lasting. After seminal papers by Lillard and Willis (1978) and Lillard and Weiss (1979), a series of recent studies such as Gottschalk and Moffit (1995), Dickens (1996) and Baker and Solon (1999), have put forward the importance of decomposing earnings inequality into persistent and transitory components. The persistent component is usually associated to the individual's life cycle earnings profile whereas the transitory component is seen as stochastic variations around this profile. The larger the permanent component, the less mobile the society, and the more unequal long-run earnings.

Latin American countries have usually been described as high inequality countries. Cross-country studies on the relationship between growth and inequality such as Deininger and Squire (1997) and Schultz (1998) have found that Latin American countries have higher inequality than countries from other regions. In addition, the 1998-1999 annual report by the Inter-American Development Bank, using cross sectional datasets, records that inequality in Latin America is not only high, but it has increased during the eighties and early nineties. However, no study has been done in the region to decompose inequality in its permanent and transitory components. This is perhaps due to the dearth of panel data for the region.

In this paper we make a decomposition of earnings inequality into permanent and transitory components, using a five-wave rotating panel from the Venezuelan Household Sampling Survey. Our aim is to explain how much of the high level of inequality in this country is due to permanent components and how much to transitory components as well as to know whether this decomposition has changed over time.

This exercise is important because it will gauge in how much the high earnings inequality observed in Latin America is due to two different, but not conflicting, stories about its causes. First high inequality in Latin America is said to be the consequence of a very unequal distribution of productive assets, in particular education. Second, high inequality can be ascribed to the unstable labour markets and macroeconomic performance of the region. The first story would imply that the permanent component is the largest within earnings inequality whereas the second story would tell that the transitory component is more important.[2]

The paper is divided into 5 sections. Section 2 describes the data while section 3 explains the earnings dynamics models in use and the estimation method applied. Section 4 includes a discussion of the results and section 5 concludes.

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[1] See for instance Katz and Autor(1999) for the U.S.A., DiNardo and Lemieux (1997) for Canada, and Schmitt (1995) for the U.K.

2. Data

The source of data for this study is the “Encuesta de Hogares por Muestreo” (Household Sampling Survey), conducted by the Venezuelan Government agency for collection and production of official statistics: Oficina Central de Estadística e Informática, OCEI (Central Bureau for Statistics and Information). This is a biannual, nationwide survey for measuring characteristics of the Venezuelan labour market as well as other demographic issues such as family composition, housing quality, access to public services and poverty. The survey is done with multi-stage sampling and the sample is rotated to avoid refusal while keeping consistency and representativeness. Each semester, one sixth of the sample is replaced by a new set of households from the same cluster that is under rotation. This feature enables researchers to produce panel data for those dwellings that remain in the sample.

We use five surveys from the first semester of 1995 to the first semester of 1997 to produce the panel data required for this study. Panel data are assembled by matching individuals with the same birth date, birth place and sex as well as the same household location code in two consecutive semesters. Given the size of the initial survey and the rotation design, the potential panel size is of around thirty thousand individuals. However, due to changes in survey size (the number of individuals interviewed declined in more than ten thousand over time), and to misrecorded/misreported identifiers, we are able to assemble a balanced panel with 7188 observations. Out of these data we keep a sub sample of males, 25 to 55 years of age in the first semester of 1995, and who have

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[2] The effect of macroeconomic instability and labour market performance upon inequality in Latin America has also been highlighted in Inter-American Development Bank (1998).

positive earnings for, at least, one semester out of the five surveyed. We chose this group of individuals, which we call “prime age males”, so that education and retirement decisions are unlikely to affect labour participation and therefore earnings. For this group of 1,105 observations we use monthly real earnings as dependent variable. This amount is self-reported by the individuals in answer to the question: How much did you earn in all your jobs last month? This is then deflated using a representative consumption price index.[3]

Despite its much smaller size, the characteristics of the panel data set are not very different from the characteristics of the initial period survey. Table 1 shows that average monthly earnings, age and schooling are very similar between the two datasets. The distribution of the samples according to occupation, industry, sector and marital status are also very akin. The only difference emerges in the distribution according to geographic region. The panel has a much larger share than the initial survey of individuals from the capital region (31.9% instead of 19.5%). On the other hand, the Guayana and Zulia regions are under-represented in the panel. This geographical bias, however, does not seem to affect the other characteristics of the data.

The Venezuelan economy has endured dismal growth performance during the last two decades and this has affected its earnings distribution. This process has produced an alarming increase in poverty rates for the period. The poverty headcount ratio has grown almost every year since 1979, with short-lived declines in the periods 1991-1993 and

[3] We used the monthly General Consumption Price Index, by OCEI. Monthly earnings were deflated by the corresponding six-month average of the index.

1997-1998.[4] Inequality indexes show a more cyclical pattern and three periods can be identified: stable inequality from 1979 to 1984, declining inequality from 1985 to 1993 and a stable but higher-than-before inequality level since 1994. As expected from inequality indexes the changes are small, usually around 0.05, for an average Gini coefficient of 0.45 for the whole period.[5] Therefore, from a historical perspective, the panel under consideration for this study corresponds to a period of high inequality.

Table 3 shows the variance-covariance matrix of Logarithmic Monthly Earnings for the “prime age males”. Three characteristics of this matrix stand apart. First, the variance of monthly earnings shows a dip in the second semester of 1995. Second, there is a large difference between the variances and the first order covariances but this difference is larger for earlier periods. Third, covariances of every order seem to increase over time.

This autocovariance structure suggests that the variance and the covariance of the variables under study are not stationary, and therefore the canonical “permanent income hypothesis” may not a good representation of Venezuelan earnings dynamics. In addition, the time varying covariances as well as the large second order covariances, suggest that just a low order serial-correlation/moving-average structure for the transitory component is perhaps not enough for explaining the time pattern of covariances. A more complex model of earnings dynamics will be needed in order to fit these autocovariance structures.

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[4] This process has been reported in several studies and despite different estimates of the level, they all coincide in reporting about a doubling of the headcount ratio for the period. See Freije(2001) and Londoño and Szekely (1997).

[5] See Freije (2001) and Londoño and Székely (1997).

In the following section we discuss some of these structures available in the literature and our estimation methodology.

Methodology

The study of earnings dynamics usually starts with a reference to the "permanent-transitory income hypothesis", introduced by Friedman and Kuznets (1954). According to this model, which we call "canonical", individuals' earnings have a permanent component that reflects personal productive characteristics associated to education, experience, abilities and preferences. On the other hand there is a transitory component that captures external factors such as business cycles and individual-specific stochastic shocks, or just plain measurement error, which make individual earnings to depart momentarily from its permanent level. This model can be expressed as:

(1) $$y_{it} = \mu_i + \varepsilon_{it}$$

where y_{it} is an income/earnings variable (more on this later) for individual "i" in period "t", μ_i is a time-invariant intercept that represents the permanent component and ε_{it} is an stochastic term that stands for the transitory component. If these two terms are assumed to be uncorrelated and the latter is independently and identically distributed across periods and individuals, then the variance of the dependent variable can be additively decomposed into the variance of the permanent component plus the variance of the transitory component. Formally, if

$$\mu_i \sim iid(\mu, \sigma_\mu^2)$$
$$\varepsilon_{it} \sim iid(0, \sigma_\varepsilon^2)$$
$$Cov(\mu_i, \varepsilon_{it}) = 0, \forall i, \forall t$$
$$Cov(\varepsilon_{it}, \varepsilon_{js}) = 0, \forall i \neq j, \forall t \neq s$$

then,

(2) $$Var(y_{it}) = \sigma_\mu^2 + \sigma_\varepsilon^2$$

and

(3) $$Cov(y_{it}, y_{it+s}) = \sigma_\mu^2, \forall s \neq t$$

In this sense, this canonical model of income dynamics is able to explain the sources of inequality. The neat decomposition of the variance of earnings allows us to state what proportion of total inequality (as measured by the variance of logarithmic earnings) is explained by inequality in the permanent component. In other words, how much of total inequality is due to time-invariant productive characteristics of individuals and how much is due to earnings instability.

However, the canonical model as stated in equation (1) and following assumptions has several shortcomings. First, it implies that inequality, as measured by the variance of log-earnings, as well as covariances of every order, are fixed over time (see equations 2 and 3). Second, assuming that the transitory component is independent over time excludes the possibility that a random shock in a given period (e.g., sickness or unemployment) may have some effects over subsequent periods. Third, assuming the permanent component is identically distributed implies that all individuals, independently of their education or training, have the same earnings growth profile and the variance of is constant over time. However, human capital models and job matching models, suggest that earnings heterogeneity must increase with age, because education and training accumulation by individuals have different rates of growth across individuals. Therefore, the variance of earnings may vary with age or job experience.

Several modifications and extensions to the canonical model can be found in the literature. MaCurdy (1982) suggests a general structure:

(4) $$y_{it} = \sum_{t=1}^{T} \lambda_t \mu_i + \varepsilon_{it}$$

(5) $$\varepsilon_{it} = \sum_{j=1}^{p} \rho_j \varepsilon_{i,t-j} + \sum_{j=0}^{q} \varphi_j \eta_{,t-j}$$

(6) $$\eta_{it} \sim N(0, \sigma^2_{\eta_t})$$

where λ_t is a weighting parameter that allows for the permanent component to have a different weight within total income each period, ρ_j is a serial correlation coefficient, φ_j is a moving average coefficient and η_{it} is a purely stochastic component.

This general structure avoids some of the problems of the canonical model. The weights λ_t allow for the variances of earnings to change over time and the covariances to vary according to order. The serial correlation and moving average coefficients make the random shock that affects an individual's income to have some permanence over time and also make the covariances to change according to order.

MaCurdy's model encompasses several studies on earnings dynamics found in the literature. For U.S. data, Lillard and Willis (1978) and Topel and Ward (1992) use an AR(1) model, Macurdy (1982) chooses a MA(2) model as well as Abowd and Card (1989) for first differences. Burkhauser et al. (1994) use a ARMA(1,1) model for U.S. and German data. None of these impose weights on the permanent component. Gottschalk and Moffitt (1995) for U.S. data, Dickens (1996) and Ramos (1999), both for U.K., estimate ARMA(1,1) models and introduce weights both for the permanent and the transitory components, actually extending the MaCurdy's structure.

The general structure implied by equations (4) to (6) assumes a fixed earnings growth profile and a fixed-over-time-and-individuals variance of the permanent component. Lillard and Weiss (1979) and, more recently, Baker (1997) and Baker and Solon (1999) introduce a much more complex permanent component, that allows for the variance of the permanent component to vary with individual specific job experience profiles.[6]

Given the availability of data and the characteristics of the variance-covariance structure of Venezuelan data described in the previous section, we start with an

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[6] Actually, the structure introduced by Baker and Solon, follows the general form $y_{it} = \lambda_t \mu_{it} + \gamma_t \varepsilon_{it}$, but the permanent component has the form $\mu_i = \alpha_i + \beta_i EXP + u_{it}$, where EXP stands for experience, u_{it} is a random walk and •it is a serially correlated term with age-related heteroskedastic variance This model, due to individual specific experience coefficients and stochastic variances, requires a large longitudinal data set.

ARMA(1,1) model with factor weights both for the permanent component and the transitory component. That is:

(7) $$y_{it} = \lambda_t \mu_i + \gamma_t \varepsilon_{it}$$

(8) $$\varepsilon_{it} = \rho \varepsilon_{it-1} + \varphi \eta_{it-1} + \eta_{it}$$

where

$$\mu_i \sim iid(\mu, \sigma_\mu^2)$$
$$\eta_{it} \sim iid(0, \sigma_\eta^2)$$
$$Cov(\mu_i, \varepsilon_{it}) = 0, \forall i, \forall t$$
$$Cov(\eta_{it}, \eta_{js}) = 0, \forall i \neq j, \forall t \neq s$$

and then the variances and covariances are[7]:

(9) $$Var(y_{it}) = \lambda_t^2 \sigma_\mu^2 + \gamma_t^2 \left(\frac{\varphi^2 + 1}{1 - \rho^2} \right) \sigma_\eta^2$$

(10) $$Cov(y_{it}, y_{it+s}) = \lambda_t \lambda_{t+s} \sigma_\mu^2 + \gamma_t \gamma_{t+s} \rho^{s-1} \left(\frac{\rho(\varphi^2 + 1)}{1 - \rho^2} + \varphi^2 \right) \sigma_\eta^2$$

This model allows for a very flexible structure of autocovariances, because the factor weights can actually make that the variances and covariances follow any time trend. Recall that the matrices described in the previous section suggest non-stationary variances as well as time varying covariances. The use of a ARMA(1,1) model is based on two reasons. First, some studies in the literature find that this low order structure fits well the data and, second, given the number of waves of the panel we only have 15 different sample autocovariances and the model of equations 7 and 8 has twelve parameters, leaving a small number of degrees of freedom for accurate fit.

The parameters of this model are estimated using a Generalized Method of Moments technique. The estimate parameters are those values that minimize the squared distance between the sample variance/covariance and the variance/covariance structure implied by the model. The goodness-of-fit test statistic for the model, as well as the standard errors for the parameters are estimated following Chamberlain (1982). Since the model defined in equations 7 and 8 nests more restricted models, such as the "canonical" or a simple AR(1) without weights, we also test the hypotheses of whether simpler models would be more adequate representations of the data.[8]

As most studies on earnings dynamics, the dependent variable of our study (i.e., y_{it} in equation 7) is the logarithm of earnings. This dependent variable, however, is defined in several ways. First we use the logarithm of earnings, after controlling for panel wave, such that any survey specific or period-specific characteristic exogenous to the individual is factored out of the earnings dynamics. In contrast to other studies on variance components decomposition, our data is collected twice a year and, thus,

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[7] Following Lillard and Willis (1978), we have assumed that the initial conditions for the variance of the transitory component are in steady state. so $Var(\varepsilon_{i1}) = \frac{\eta}{1-\rho^2}$.

seasonality of earnings may be an issue and by introducing a panel-wave dummy we control for this factor. Then we use the residuals from two additional regressions: first, a regression of earnings on a quartic of age, schooling and migration and, second, a regression of earnings on the former variables and additional job characteristics such as occupation, industry, unionization, sector and marital status. This allows us to measure how much of the permanent and transitory components is explained by characteristics associated to human capital formation and other observables associated to labour market performance. Finally, we repeat the same experiments with a sample of "job attached" individuals and use hourly wages as dependent variable. By focusing on wages only, we leave aside the additional sources of dispersion due to the variance of hours and the covariance between hours of work and earnings.

4. Estimation Results

Table 4 summarizes the goodness of fit statistics for different models and the different definitions of residual earnings. The first thing to notice is that a full weights model (i.e., a model with factor weights both for the transitory and the permanent component) has a much worse fit than all other models, for every database. In addition, the factor weights for the transitory component are always estimated equal to zero. Secondly, the test statistics for the ARMA(1,1) and the AR(1) models are very similar. This is because every estimation with an ARMA(1,1) structure for the transitory component results in a moving-average parameter equal to zero. This two results lead us

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[8] See appendix for a more formal explanation of the estimation technique.

to concentrate on the parameter estimates for the half weights (that is, factor weights only for the permanent component), no weights and canonical models with an AR(1) process .

Table 5, 6 and 7 contain the parameter estimates and its standard errors for the three models with best fit and the three earnings residuals definitions. There are several results that can be derived from these tables. First, the coefficient for serial correlation is significantly different from zero but the factor weights for the permanent component are not significantly different from one, for the three databases. This structure of factor weights actually allows for a dip in the variance in the second period as we reported in the description of the data. In addition, the small serial correlation parameter, explains the large difference between the variances and first covariances. Figure 1 shows how the fitted values follow the sample autocovariances for earnings residuals after controlling for panel waves using the parameters from the half weights model.

With these parameter estimates, we can decompose inequality, as measured by the variance of log earnings, as follows. From equation (9) we have:

$$Var(y_{it}) = \lambda_t \sigma_\mu^2 + \left(\frac{1}{1-\rho^2}\right)\sigma_\eta^2$$

then, dividing both sides of the equation by $Var(y_{it})$ and manipulating the right hand term:

$$1 = \left(\frac{\lambda_t \sigma_\mu^2}{Var(y_{it})}\right) + \left(\frac{\sigma_\eta^2}{Var(y_{it})}\right) + \left(1 - \left(\frac{\lambda_t \sigma_\mu^2}{Var(y_{it})}\right) - \left(\frac{\sigma_\eta^2}{Var(y_{it})}\right)\right)$$

where the first term in the right hand side is the share of the permanent component, the second is the share of the stochastic component, and the third is the residual ascribed to the serial correlation component. Notice that this decomposition implies that both the stochastic and the serial correlation components are fixed thus changes in the variance are due to changes in the participation of the permanent components through its factor weights. Figure 2 shows how the dip in the variance of earnings as well as the rise in the second semester of 1996 is totally due to changes in the permanent component.

Table 8, decomposes total earnings variance into permanent, transitory and serial correlation components for the three earning residuals definitions. The first three columns show that the stochastic component share within earnings inequality has varied from a maximum of 82.7% in the second semester of 1995 to a minimum of 71.7 % in the second semester of 1996. The share of the variance of the permanent component oscillates between 16.2% and 27.2%.[9] Furthermore, the share of the permanent component declines with the introduction of observable characteristics of the individuals. The three last columns of table 8 show that the variance of the permanent component represents less than 14% for earnings residuals after controlling for all observables.

Instead, we may also decompose log-earnings variance using the no-weight AR(1) model. This model has similar fit to the half weights model and all its coefficients are significantly different from zero. In this case, both the permanent and transitory components have a fixed share within log-earnings variance: 21.3% for the variance of permanent component, 77.6% for the variance of the stochastic component, the remaining

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[99] The serial correlation component is small and stable.

1.1% for the serial correlation component. The message is the same: the stochastic component has the largest share within total inequality.

Another aspect that we derive from the parameter estimates of tables 5 to 7 is that the introduction of human capital and labour market observable characteristics has a larger effect on the variance of the permanent component (i.e., σ_{μ}^{2}) than on the variance of the stochastic component (i.e. σ_{η}^{2}). Actually, the variance of the permanent component falls from 3.2 to 2.9 when controlling for age, education and migration status, and to 1.9 after controlling for additional labour market characteristics. On the other hand, the variance of the stochastic component declines from 13.4, to 13.3 and 12.5, respectively. In other words, the variance of the permanent component declines in 41% but the variance of the stochastic component only falls in 7%.

These results show a picture of highly mobile real monthly earnings in Venezuela. Despite some oscillations, the share of the variance of permanent component is always smaller than the share of the variance of the stochastic component. This result contrasts with findings from studies for developed countries where the share of the permanent component is larger or at least as large as the transitory component. The only exception is the case of Germany during the mid eighties, reported by Burkhauser et al (1997), where the permanent component is found to represent around 8% of the earnings variance.

The presence of this large transitory component has two possible interpretations. On the one hand it implies that there is a great deal of earnings mobility among Venezuelan prime age males and, consequently, the high inequality measured from cross-sectional data for this country does not necessarily involve an equally high long-term inequality. In other words, individuals change their position within the earnings distribution a great deal. On the other hand, this large transitory component also implies that lower levels of cross-sectional inequality could be achieved if the economy had a more stable labour market and macroeconomic performance.

The three years that our panel-data span, are particularly unstable. Real GDP grew 3.4% in 1995, declined 1.6% in 1996 and it rose again 1997 by 5.6%. Inflation went from 56.6% in 1995, to 103.2 % in 1996 and 37.6% in 1997. Unemployment rates went from 10.2% in 1995 to 12.4% in 1996 and then down to 10.6% in 1997. Between 1994 and 1995, the country underwent a severe financial crisis that affected more than 50% of the banking sector. Then, in 1997, the exchange rate was devalued in more than 30%, and a new labour law that made firing decisions cheaper was introduced. In other words, this is a highly unstable period and, perhaps, this is the cause for such a large transitory component within earnings inequality.

We must also take into consideration that the variance of monthly earnings is affected by the variation of monthly hours and the covariance between earnings and hours of work. Given the instability of the period under study, we should expect that there is a large variation of hours of work which reflects on the large transitory component of monthly earnings. In order to evaluate the effect of hours of work, in the following section we concentrate on a sub sample of individuals more attached to the labour market. The comparison between the decompositions for these two samples will shed some light on the importance of hours employment into the large transitory component of monthly earnings.

4.1 *A decomposition of hourly wages*

We create a panel of males in the same age group but who work no less than thirty hours a week, during the five semesters under study. For this group, that we call “job-attached prime age males”, we use hourly wages as dependent variable. Hourly wages are computed dividing monthly earnings by hours of work during previous month (which is computed as 4.3 times the weekly hours answered to the question “How many hours did you work last week?”) This subsample of only 656 observations has much less variation in number of hours worked than the previous sample and thus most of the variation in the dependent variable should not be greatly affected by changes in hours of work.

Table 9 shows the main characteristics for of this sample over the five waves. When compared to table 2 we notice that this dataset is similar to the former one we used. Real monthly earnings and real hourly wages decline sharply over time in both samples. The same happens to coverage of collective agreements. Earnings and average age and schooling, as well as the distribution according to occupation, industry, region and marital status are almost the same between the samples. However, the “job-attached” group has a larger share of migrants and employers, as well as a larger share of individuals covered by collective agreement.

Table 10 shows the parameter estimates for log-hourly wages after controlling for panel wave, under the same models applied before. Surprisingly, we find a similar distribution of the variance of wages into permanent and transitory components. The former has around 23% and the latter accounts for the remaining 77%. An important difference, however, is that the coefficient for serial correlation is no longer significant. This suggests that variation in hours of work is the source of the serial correlation structure for the transitory component in monthly earnings. That is to say that changes in hours of work have some persistent effect on earnings over time, though small. When focusing on hourly wages for job-attached workers the serial correlation vanishes.

It is remarkable that even focusing on always-employed people, the transitory component is so dominant. There are three possible reasons for this. First, inflationary shocks, which suddenly change real wages may induce a lot of variability if workers are not able, as they usually are not, to fully index their wages. Given the large price increases experienced during this period, this is a plausible explanation. Second, a recession not only affects the number of people employed through a decline of labour but it also induces, unless there is a proportionate change in labour supply, a decline in the equilibrium real wages. Third, under a dual labour market, it may be the case that individuals keep working all periods, but move to the less-productive sector where they work more hours for lower ages in order to keep the same earnings. All these three cases induce instability of real hourly wages, which is consistent with our findings of a large transitory component in the variance of hourly wages.

5. Summary and Conclusions

In this paper we estimate several error component models in order to decompose earnings inequality in Venezuela into its permanent and transitory components. Using a Venezuelan five-wave rotating panel of prime age males spanning years 1995 to 1997 we apply a Generalized Method of Moments for the estimation and inference of several error components specifications.

The decomposition of the variance of log earnings into permanent and transitory components allows us to gauge how much inequality is due to the dispersion of individual's earnings associated to permanent personal productivity characteristics or to stochastic variations due to earnings instability. A large permanent component would imply that earnings inequality is long lasting and individuals do not frequently change their position in the earnings distribution over time.

After fitting several models, we find that the permanent component represents around 22% of earnings inequality as measured by the variance of logarithmic real monthly earnings, whereas the stochastic component accrues for 77% and the remaining 1% corresponds to serial correlation. Similar figures emerge when decomposing logarithmic hourly wages. This results contrast to the findings of the error components literature for developed countries where the permanent component has been found larger or at least as large as the transitory component, for instance Baker and Solon(1999), Dickens (1996), Gottschalk and Moffitt (1995).

This large transitory component can be the consequence of the instability that characterizes the Venezuelan economy during this period. This country endured unemployment rates above 10% for the three years under study, inflation above 100% and GDP decline in 1996. This instability affects the labour market in two ways. First it induces large variations in hours of work which have an effect on earnings instability. Second, it provokes abrupt oscillations of real wage rates through inflation and declining productivity.

The presence of this large transitory component has two possible interpretations. On the one hand it implies that there is a great deal of earnings mobility among Venezuelan prime age males and, consequently, the high inequality measured from cross-sectional data for this country does not necessarily involve an equally high long-term inequality. In other words, individuals change their position within the earnings distribution a great deal. On the other hand, this large transitory component also implies that lower levels of short-term inequality could be achieved if the economy had a more stable labour market and macroeconomic performance.

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Table 1

Comparison between panel and cross section data

	1st, 1995	
	Panel (1105 obs.)	**Cross Section (15524 obs)**
Average Monthly Earnings (in 1997 Bs.)	111580.5	113189
Average monthly hours of work	164	161
Standrad deviation of monthly hours of work	76	77
Average Age (in years)	38.4	37.4
Average Schooling (in years)	7.3	7.6
Migrant	32.5%	35.2%
Covered by colective bargaining agreement	19.1%	15.6%
Occupations:		
Professionals	7.2%	8.9%
Firms Managers and Elected Officials	3.9%	4.9%
Office Clerks and Salespersons	21.5%	19.4%
Agricultural workers	9.7%	9.8%
Miners	0.1%	1.0%
Drivers, machinists and sailors	13.0%	12.7%
Craft and related	25.5%	25.0%
Plant and Machine Operatives	7.2%	5.0%
Personal and Protective services	10.5%	9.9%
Armed Forces and consular officers	0.3%	0.7%
Not working or Not reporting	1.1%	2.5%
Industries:		
Agriculture, Forestry and Fishing	10.2%	10.0%
Mining and Oil Industry	0.6%	2.3%
Manufacturing	17.6%	16.3%
Energy & Water Supply	1.5%	1.1%
Contruction	13.4%	14.5%
Distribution, hotels and catering	18.9%	18.3%
Transport and telecomunications	9.6%	9.8%
Banking and Finance	5.4%	4.8%
Other Services	21.6%	20.4%
Not working or Not reporting	1.1%	2.5%
Regions:		
Capital	31.9%	18.8%
Central	10.1%	13.3%
North Eastern	12.7%	8.7%
Guayana	2.4%	16.0%
Savanah	4.1%	4.1%
Andes	11.7%	10.8%
North Western	16.8%	13.3%
Zulia	10.3%	15.1%
Sector:		
Government white collar worker	10.9%	10.8%
Government blue collar worker	4.0%	4.3%
Private firm white collar worker	14.3%	16.3%
Private firm blue collar worker	30.4%	27.0%
Cooperative worker	0.5%	0.5%
Self employed	31.5%	31.0%
Employer	7.1%	7.3%
Not working or Not reporting	1.3%	2.9%
Marital Status:		
Married or Couple	75.0%	72.5%
Divorced/Widowed	2.5%	2.7%
Single	22.5%	24.8%

Table 2

Characterstics for males aged 25 to 55, with positive earnings for at least one period

	1st, 1995	2nd,1995	1st, 1996	2nd,1996	1st, 1997
Average Montlhy Earnings (in 1997 Bs.)	111580.5	106243.9	90103.5	81415.1	84008.6
Average monthly hours of work	164	169	168	169	169
Standrad deviation of monthly hours of work	76	71	68	71	74
Average Age (in years)	38.4	38.9	39.4	39.9	40.4
Average Schooling (in years)	7.3	7.4	7.5	7.5	7.5
Migrant	32.5%	32.5%	32.5%	32.5%	32.5%
Covered by colective bargaining agreement	19.1%	16.5%	15.3%	16.5%	16.1%
Occupations:					
Professionals	7.2%	8.0%	8.1%	8.4%	7.6%
Firms Managers and Elected Officials	3.9%	3.3%	3.3%	4.2%	3.8%
Office Clerks and Salespersons	21.5%	22.2%	19.7%	17.5%	18.9%
Agricultural workers	9.7%	10.4%	9.7%	10.4%	9.8%
Miners	0.1%	0.3%	0.3%	0.5%	0.5%
Drivers, machinists and sailors	13.0%	12.9%	14.2%	14.8%	15.3%
Craft and related	25.5%	24.7%	27.3%	25.7%	24.6%
Plant and Machine Operatives	7.2%	6.1%	5.3%	5.7%	5.9%
Personal and Protective services	10.5%	10.6%	10.9%	11.2%	11.9%
Armed Forces and consular officers	0.3%	0.5%	0.3%	0.5%	0.3%
Not working or Not reporting	1.1%	1.3%	0.9%	1.2%	1.5%
Industries:					
Agriculture, Forestry and Fishing	10.2%	10.8%	10.0%	10.0%	10.0%
Mining and Oil Industry	0.6%	0.7%	1.2%	1.2%	1.2%
Manufacturing	17.6%	17.0%	15.3%	16.1%	15.3%
Energy & Water Supply	1.5%	1.2%	1.4%	1.6%	1.4%
Contruction	13.4%	12.9%	13.7%	13.7%	13.7%
Distribution, hotels and catering	18.9%	19.6%	16.8%	17.2%	16.8%
Transport and telecomunications	9.6%	8.9%	11.9%	10.8%	11.9%
Banking and Finance	5.4%	5.7%	7.1%	6.2%	7.1%
Other Services	21.6%	21.9%	21.1%	22.1%	21.1%
Not working or Not reporting	1.1%	1.3%	1.5%	1.1%	1.5%
Regions:					
Capital	31.9%	31.9%	31.9%	31.9%	31.9%
Central	10.1%	10.1%	10.1%	10.1%	10.1%
North Eastern	12.7%	12.7%	12.7%	12.7%	12.7%
Guayana	2.4%	2.4%	2.4%	2.4%	2.4%
Savanah	4.1%	4.1%	4.1%	4.1%	4.1%
Andes	11.7%	11.7%	11.7%	11.7%	11.7%
North Western	16.8%	16.8%	16.8%	16.8%	16.8%
Zulia	10.3%	10.3%	10.3%	10.3%	10.3%
Sector:					
Government white collar worker	10.9%	10.6%	10.0%	10.4%	9.1%
Government blue collar worker	4.0%	4.4%	4.7%	4.5%	4.5%
Private firm white collar worker	14.3%	13.5%	13.3%	12.1%	14.6%
Private firm blue collar worker	30.4%	29.4%	26.7%	29.4%	28.7%
Cooperative worker	0.5%	0.8%	1.6%	2.6%	2.4%
Self employed	31.5%	32.7%	35.4%	33.3%	32.6%
Employer	7.1%	7.1%	7.3%	6.5%	6.8%
Not working or Not reporting	1.3%	1.5%	1.0%	1.2%	1.4%
Marital Status:					
Married or Couple	75.0%	74.1%	74.9%	74.3%	73.7%
Divorced/Widowed	2.5%	3.1%	2.4%	3.4%	3.5%
Single (omitted)	22.5%	22.9%	22.7%	22.3%	22.8%

Table 3

Variance Covariance Matrix of log Monthly Earnings, for "prime age" males

	1st semester, 1995	2nd semester, 1995	1st semester, 1996	2nd semester, 1996	1st semester, 1997
1st semester, 1995	18.317				
2nd semester, 1995	4.234	14.711			
1st semester, 1996	3.203	3.865	17.644		
2nd semester, 1996	3.381	3.801	6.397	18.124	
1st semester, 1997	2.866	3.719	5.127	6.275	17.666

Table 4
Goodness of Fit for the models using Log Monthly Earnings [1].
(number of observations: 1105)

	Chi-squared [3]		Degrees of freedom
Log. Monthly Earnings for males aged 25 to 55, after controling for panel wave			
Full Weights ARMA(1,1): $_t$ + $_t$($_{t-1}$+ $_{t-1}$+ $_t$)	532.00		3
Half Weights ARMA(1,1): $_t$ + ($_{t-1}$+ $_{t-1}$+ $_t$)	16.84	*	7
No Weights ARMA(1,1): + ($_{t-1}$+ $_{t-1}$+ $_t$)	22.93	*	11
Full Weights ARMA(1,0): $_t$ + $_t$($_{t-1}$+ $_t$)	532.00		4
Half Weights ARMA(1,0): $_t$ +($_{t-1}$+ $_t$)	16.84	*	8
No Weights ARMA(1,0): +($_{t-1}$+ $_t$)	22.93	*	12
Canonical: + $_t$	41.35		13
Log. Monthly Earnings for males aged 25 to 55, after controling for panel wave, age, schooling and migration			
Full Weights ARMA(1,1): $_t$ + $_t$($_{t-1}$+ $_{t-1}$+ $_t$)	535.55		3
Half Weights ARMA(1,1): $_t$ + ($_{t-1}$+ $_{t-1}$+ $_t$)	16.76	*	7
No Weights ARMA(1,1): + ($_{t-1}$+ $_{t-1}$+ $_t$)	23.07	*	11
Full Weights ARMA(1,0): $_t$ + $_t$($_{t-1}$+ $_t$)	535.55		4
Half Weights ARMA(1,0): $_t$ +($_{t-1}$+ $_t$)	16.76	*	8
No Weights ARMA(1,0): +($_{t-1}$+ $_t$)	23.07	*	12
Canonical: + $_t$	40.38		13
Log. Monthly Earnings for males aged 25 to 55, after controling for panel wave, age, schooling, migration and labor market characteristics [2]			
Full Weights ARMA(1,1): $_t$ + $_t$($_{t-1}$+ $_{t-1}$+ $_t$)	516.51		3
Half Weights ARMA(1,1): $_t$ + ($_{t-1}$+ $_{t-1}$+ $_t$)	13.59	**	7
No Weights ARMA(1,1): + ($_{t-1}$+ $_{t-1}$+ $_t$)	18.61	**	11
Full Weights ARMA(1,0): $_t$ + $_t$($_{t-1}$+ $_t$)	516.51		4
Half Weights ARMA(1,0): $_t$ +($_{t-1}$+ $_t$)	13.59	**	8
No Weights ARMA(1,0): +($_{t-1}$+ $_t$)	18.61	**	12
Canonical: + $_t$	27.79		13

Notes:

(1) The Null Hypothesis, Ho: =0, is tested with the quadratic form $N(\pi - g(\theta))' W^{-1}(\pi - g(\theta))$, which follows a chi-squared distribution with (T*(T+1)/2) - P) degress of freedom., where N is the number of observations, T is the number of waves of the panel, P is the number of parameters in vector , g( ) is a function of the parameter vector derived from the respective error component model, is a vector derived from the lower triangle of the variance-covariance matrix from the sample and W is the matrix of fourth moments of .

(2) The labor market characteristics are: occupation, industry, collective bargaining agreement coverage, function (e.g., government employee, self employed, employer, etc.), region and marital status.

(3) ** (*) stands for failure to reject the null hypothesis with 5% (1%) significance level

Table 5

Parameter estimates for Log Monthly Earnings
Controling for panel wave

	Canonical		No weights AR(1)		Half weights AR(1)	
		S.E.		S.E.		S.E.
2	4.355 **	0.335	3.761 **	0.375	3.205 **	0.702
2	12.429 **	0.468	13.472 **	0.521	13.417 **	0.527
			0.121 **	0.027	0.116 **	0.028
1					1	
2					0.906	0.152
3					1.176	0.181
4					1.262	0.183
5					1.126	0.170

Note: ** (*) Significantly different from 0, or from 1 for the factor weights, at 5% (10%) significance level

Table 6

Parameter estimates for Log Monthly Earnings residuals,
controling for age, education and migration

	Canonical		No weights AR(1)		Half weights AR(1)	
		S.E.		S.E.		S.E.
2	4.084 **	0.324	3.491 **	0.374	2.926 **	0.696
2	12.435 **	0.132	13.418 **	0.521	13.374 **	0.528
			0.116 **	0.027	0.114 **	0.028
1					1	
2					0.881	0.164
3					1.213	0.200
4					1.251	0.198
5					1.161	0.188

Note: ** (*) Significantly different from 0, or from 1 for the factor weights, at 5% (10%) significance level

Table 7

Parameter estimates for Log Monthly Earnings residuals,
controling for age, education, migration and labor market characteristics

	Canonical		No weights AR(1)		Half weights AR(1)	
		S.E.		S.E.		S.E.
2	2.633 **	0.240	2.247 **	0.366	1.866 **	0.689
2	11.865 **	0.456	12.507 **	0.524	12.479 **	0.529
			0.082 **	0.029	0.081 **	0.030
1					1	
2					0.867	0.253
3					1.282	0.320
4					1.287	0.314
5					1.131	0.288

Note: ** (*) Significantly different from 0, or from 1 for the factor weights, at 5% (10%) significance level

Table 8

Decomposition of Fitted Variance into Transitory and Permanent Components For Monthly Earnings

Panel Wave	For Log Monthly Earnings, after controling for panel wave			For Residuals of Log Monthly Earnings, controling for age, school, migration and panel wave			For residuals of Log Monthly Earnings, controling for age, school, migration, panel wave and labor market characteristics		
	Permanent Component	Stochastic Component	Serial Correlation Component	Permanent Component	Stochastic Component	Serial Correlation Component	Permanent Component	Stochastic Component	Serial Correlation Component
1st semester, 1995	19.1%	79.8%	1.1%	17.8%	81.2%	1.1%	12.1%	80.7%	7.3%
2nd semester, 1995	16.2%	82.7%	1.1%	14.3%	84.5%	1.1%	9.3%	83.2%	7.5%
1st semester, 1996	24.6%	74.4%	1.0%	24.1%	74.9%	1.0%	18.4%	74.9%	6.7%
2nd semester, 1996	27.3%	71.7%	1.0%	25.3%	73.8%	1.0%	18.5%	74.8%	6.7%
1st semester, 1997	23.0%	76.0%	1.0%	22.5%	76.5%	1.0%	14.9%	78.1%	7.0%

Table 9

Charactersitics for males aged 25 to 55, working 30 hours or more in five periods

	1st, 1995	2nd,1995	1st, 1996	2nd,1996	1st, 1997
Average Hourly Wages (in 1997 Bs.)	3160.2	2700.7	2372.7	2240.0	2226.3
Average monthly hours of work	195	196	194	195	198
Standrad deviation of monthly hours of work	41	41	35	37	42
Average Age (in years)	38.7	39.1	39.6	40.1	40.6
Average Schooling (in years)	7.4	7.5	7.7	7.7	7.6
Migrant	35.4%	35.4%	35.4%	35.4%	35.4%
Covered by colective bargaining agreement	21.6%	18.9%	17.8%	18.6%	17.2%
Occupations: Professionals	7.5%	8.5%	8.7%	8.5%	7.9%
Firms Managers and Elected Officials	4.3%	4.0%	3.7%	4.6%	5.0%
Office Clerks and Salespersons	23.0%	23.8%	21.5%	19.2%	20.4%
Agricultural workers	10.4%	10.7%	10.5%	11.0%	9.9%
Miners	0.2%	0.2%	0.2%	0.3%	0.2%
Drivers, machinists and sailors	11.1%	11.9%	13.0%	15.4%	15.7%
Craft and related	24.4%	22.7%	25.3%	22.7%	22.6%
Plant and Machine Operatives	6.7%	5.6%	5.2%	5.6%	5.5%
Personal and Protective services	12.2%	12.4%	11.7%	12.2%	12.7%
Armed Forces and consular officers	0.3%	0.3%	0.3%	0.3%	0.3%
Industries: Agriculture, Forestry and Fishing	10.7%	11.1%	10.5%	11.0%	10.5%
Mining and Oil Industry	0.9%	0.9%	0.9%	0.8%	0.9%
Manufacturing	17.7%	17.2%	16.3%	16.0%	16.3%
Energy & Water Supply	1.5%	1.5%	1.4%	2.0%	1.4%
Contruction	11.1%	9.9%	11.0%	10.4%	11.0%
Distribution, hotels and catering	21.0%	21.7%	18.5%	18.5%	18.5%
Transport and telecomunications	8.8%	8.5%	12.5%	11.7%	12.5%
Banking and Finance	5.6%	6.1%	7.8%	7.3%	7.8%
Other Services	22.4%	23.0%	21.0%	22.4%	21.0%
Not working or Not reporting	0.0%	0.0%	0.0%	0.0%	0.2%
Regions: Capital	34.8%	34.8%	34.8%	34.8%	34.8%
Central	8.5%	8.5%	8.5%	8.5%	8.5%
North Eastern	13.9%	13.9%	13.9%	13.9%	13.9%
Guayana	3.1%	3.1%	3.1%	3.1%	3.1%
Savanah	3.4%	3.4%	3.4%	3.4%	3.4%
Andes	11.6%	11.6%	11.6%	11.6%	11.6%
North Western	15.1%	15.1%	15.1%	15.1%	15.1%
Zulia	9.8%	9.8%	9.8%	9.8%	9.8%
Sector: Government white collar worker	11.3%	11.7%	11.0%	11.6%	10.5%
Government blue collar worker	3.5%	4.1%	4.7%	4.4%	4.1%
Private firm white collar worker	15.9%	14.0%	13.7%	13.4%	15.4%
Private firm blue collar worker	29.3%	29.0%	26.1%	27.7%	26.1%
Cooperative worker	0.5%	0.8%	1.5%	2.3%	1.7%
Self employed	30.0%	31.0%	33.8%	32.3%	33.5%
Employer	9.3%	9.5%	9.2%	8.1%	8.7%
Not working or Not reporting	0.3%	0.0%	0.0%	0.2%	0.0%
Marital Status: Married or Couple	78.4%	78.5%	79.1%	78.5%	78.1%
Divorced/Widowed	2.7%	2.7%	2.7%	3.4%	3.4%

Single (omitted)	18.9%	18.8%	18.1%	18.1%	18.6%

Table 10

Parameter estimates for Log Hourly Wages

Controling for panel wave

	Canonical		No weights AR(1)		Half weights AR(1)	
		S.E.		S.E.		S.E.
^{2}	0.352 **	0.047	0.355 **	0.038	0.063	0.040
^{2}	1.1794 **	0.100	1.173 **	0.081	1.210 **	0.082
			-0.010	0.042	-0.039	0.042
$_{1}$					1	
$_{2}$					1.696 *	0.366
$_{3}$					4.095 **	0.656
$_{4}$					3.178 **	0.606
$_{5}$					3.571 **	0.660

Note: ** (*) Significantly different from 0, or from 1 for the factor weights, at 5% (10%) significance level

Table 11

Regressions of Log Monthly Earnings

Number of Observations	5529			5529			5529		
R^2	0.0040			0.0223			0.1500		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Constant	9.391	**	0.126	-96.204	**	30.999	-56.684	*	28.965
Panel waves: 1st wave' 1995 (omitted)									
2nd wave' 1995	-0.085		0.180	-0.072		0.178	-0.119		0.166
1st wave' 1996	0.109		0.179	0.133		0.178	0.064		0.165
2nd wave' 1996	0.657	**	0.171	0.715	**	0.170	0.663	**	0.158
1st wave' 1997	0.300	*	0.180	0.385	**	0.180	0.255		0.169
Human Capital: Age (in years)				10.300	**	3.202	6.613	**	3.000
Age^2				-0.371	**	0.122	-0.248	**	0.115
Age^3				0.006	**	0.002	0.004	**	0.002
Age^4				0.000	**	0.000	0.000	**	0.000
Schooling (in years)				0.079	**	0.017	0.042	**	0.019
Migrant (omitted)									
Non-Migrant				-0.688	**	0.117	-0.183		0.119
Covered by colective bargaining agreement							1.492	**	0.157
Occupation: Professionals							0.160		0.268
Firms Managers and Elected Officials							1.145	**	0.281
Office Clerks and Salespersons							0.161		0.232
Agricultural workers							0.226		0.447
Miners							0.425		0.939
Drivers, machinists and sailors							0.189		0.240
Craft and related (omitted)									
Plant and Machine Operatives							-0.271		0.271
Personal and Protective services							0.094		0.233
Armed Forces and consular officers							0.636		1.136
Not working or Not reporting							-0.926		1.404
Industry:									
Agriculture, Forestry and Fishing							0.257		0.446
Mining and Oil Industry							1.271	**	0.588
Manufacturing							-0.078		0.244
Energy & Water Supply							-0.677		0.589
Contruction							-0.841	**	0.269
Distribution, hotels and catering (omitted)									
Transport and telecomunications							0.309		0.284
Banking and Finance							0.135		0.257
Other Servics							-0.067		0.229
Not working or Not reporting							-1.304	*	0.786
Regions: Capital (omitted)									
Central							-1.541	**	0.204
North Eastern							-0.554	**	0.171
Guayana							0.519	**	0.218
Savanah							-0.741	**	0.253
Andes							-0.765	**	0.183
North Western							-1.634	**	0.183
Zulia							-1.393	**	0.210

Table 11 (continued)

Regressions on Log Monthly Earnings

Sector: Government white collar worker (omitted)						
Government blue collar worker					-0.895 **	0.341
Private firm white collar worker					0.757 **	0.262
Private firm blue collar worker					0.821 **	0.261
Cooperative worker					0.973 *	0.497
Self employed					1.364 **	0.257
Employer					1.763 **	0.323
Not working or Not reporting					-6.227 **	1.106
Marital Status: Married					0.918 **	0.155
Couple					1.220 **	0.162
Divorced/Widowed					0.524	0.341
Single (omitted)						

Notes:

** (*) Significantly different from 0 at 5% (10%) significance level

Table 12

Regressions on Log. Hourly wages

Number of Observations	3280			3280			3280		
R^2	0.0175			0.0578			0.1408		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Constant	5.728	**	0.057	26.469	*	13.564	19.331		13.490
Panel waves: 1st wave' 1995 (omitted)									
2nd wave' 1995	-0.010		0.082	-0.013		0.080	-0.003		0.077
1st wave' 1996	-0.036		0.087	-0.037		0.086	-0.047		0.082
2nd wave' 1996	0.391	**	0.071	0.399	**	0.070	0.390	**	0.068
1st wave' 1997	0.364	**	0.080	0.378	**	0.078	0.376	**	0.076
Human Capital: Age (in years)				-2.201		1.421	-1.363		1.408
Age^2				0.083		0.055	0.049		0.054
Age^3				-0.001		0.001	-0.001		0.001
Age^4				0.000		0.000	0.000		0.000
Schooling (in years)				0.060	**	0.008	0.035	**	0.009
Migrant (omitted)									
Non-Migrant				-0.321	**	0.050	-0.076		0.052
Covered by colective bargaining agreement							0.124	*	0.069
Occupation: Professionals							0.042		0.136
Firms Managers and Elected Officials							0.298	**	0.148
Office Clerks and Salespersons							-0.189	*	0.106
Agricultural workers							-0.216		0.174
Miners							0.474	**	0.235
Drivers, machinists and sailors							-0.096		0.121
Craft and related (omitted)									
Plant and Machine Operatives							-0.118		0.118
Personal and Protective services							-0.294	**	0.096
Armed Forces and consular officers							0.733	**	0.207
Not working or Not reporting							-5.362	**	0.177
Industry: Agriculture, Forestry and Fishing							0.735	**	0.192
Mining and Oil Industry							0.003		0.167
Manufacturing							0.662	**	0.194
Energy & Water Supply							-0.204	*	0.113
Contruction							-0.192		0.286
Distribution, hotels and catering (omitted)									
Transport and telecomunications							-0.074		0.150
Banking and Finance							0.203	*	0.106
Other Servics							-0.086		0.112
Not working or Not reporting							-1.069		0.892
Regions: Capital (omitted)									
Central							-0.515	**	0.100
North Eastern							-0.512	**	0.082
Guayana							-0.091		0.092
Savanah							-0.414	**	0.075
Andes							-0.488	**	0.089
North Western							-0.875	**	0.102
Zulia							-0.659	**	0.102

Table 12 (continued)

Regressions on Log. Hourly Wages

Sector: Government white collar worker (omitted)							
Government blue collar worker					-0.059		0.136
Private firm white collar worker					0.017		0.118
Private firm blue collar worker					0.117		0.110
Cooperative worker					0.147		0.269
Self employed					0.156		0.113
Employer					0.192		0.161
Not working or Not reporting					-5.475	**	0.199
Marital Status: Married					0.385	**	0.079
Couple					0.356	**	0.081
Divorced/Widowed					0.272	*	0.163
Single (omitted)							

Notes:
** (*) Significantly different from 0 at 5% (10%) significance level

Figure 1
Sample (__) and Fitted (_ _) Autocovariances for Log Monthly Earnings, after controling for panel wave

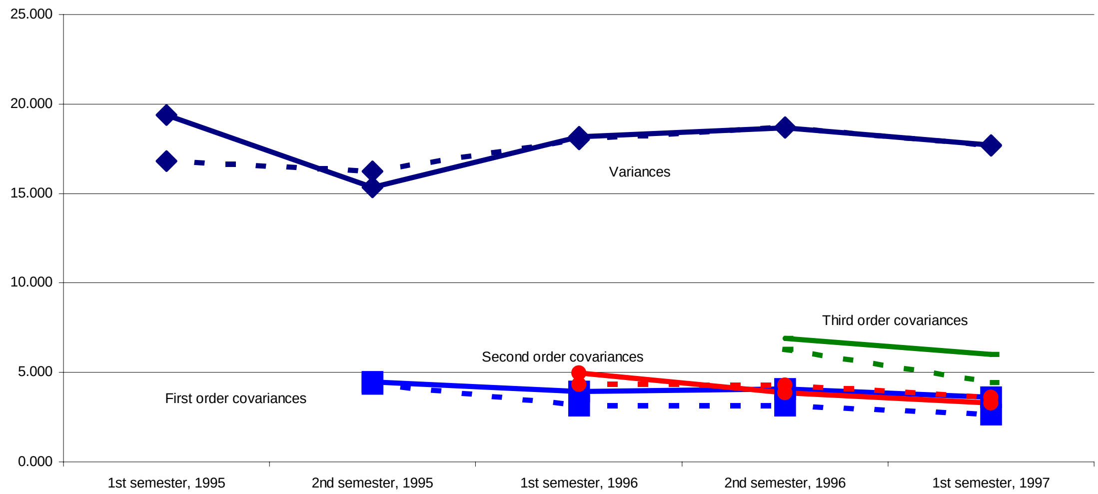
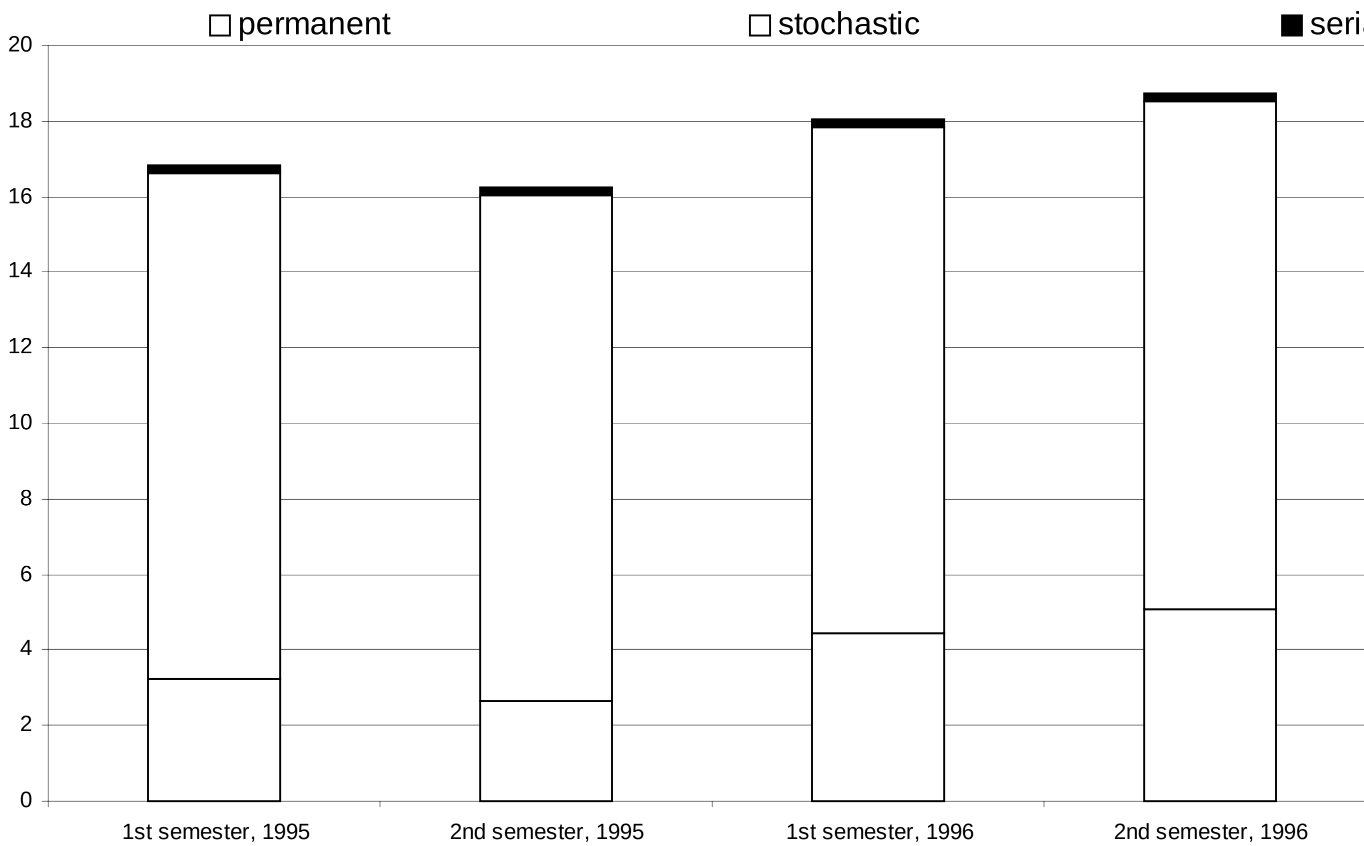


Figure2
Decomposition of Fitted Variance of log Earnings, controling for panel wave



Appendix

In this appendix we summarize the estimation and inference methodology used throughout the paper.

The residuals used for estimation of sample autocovariances, are obtained from a OLS regression of the form:

$$y_{it} = \beta' X + u_{it}$$

with pooled data for the five periods. The residuals are then defined as:

$$\hat{u}_{it} = y_{it} - \hat{\beta}' X$$

where the coefficients sitting in change for different cases. First we only include panel-wave dummies, then we add a quartic in age, education and migration status, and in the third stage we add occupation, industry, region, function and marital status. Tables 11 and 12 show the coefficient estimates for monthly earnings and hourly wages.

With these residuals we compute a sample autocovariance matrix, of dimension TxT, where T is the number of panel waves (in our case, 5). Stacking the lower triangular matrix of this autocovariance matrix we define a column vector of dimension T(T+1)/2 (in our case, 15). On the other hand, from equations 9 and 10 in the text, we define a column vector g( ), with the same dimension as , which consist of a series of linear or non-linear restrictions on the vector of parameters . The dimension of , Px1, depends on the error components model chosen, ranging from 2x1 for the canonical to 12x1 for the full-weights ARMA(1,1) model.

The parameters are estimated by minimizing the expression $(\pi - g(\theta))' \Psi^{-1} (\pi - g(\theta))$, where Ψ^{-1} is a weighting matrix. In our case, we use the matrix of fourth moments of the fitted residuals as weighting matrix, following the procedure described in the appendix of Abowd and Card (1989).

The goodness of fit of the model is tested with the statistic $N(\pi - g(\theta^*))' \Psi^{-1} (\pi - g(\theta^*))$, where N is the number of observations in the panel, which follows a chi-squared distribution with [T(T+1)/2]-P degrees of freedom.

Finally, the standard errors are obtained from the diagonal of the matrix $(g'(\theta^*))' \Psi^{-1} (g'(\theta^*))$, where $g'(\theta^*)$ stands for the jacobian of $g(\theta)$ evaluated at the parameter estimates.

For a formal discussion of the estimation and inference techniques see Chamberlain (1982)