Informality and Poverty: Are these Processes Dynamically Interrelated? The case of Argentina

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ABSTRACT

Poverty and informal employment are often regarded as correlated phenomena. Many empirical studies have shown that informal employment has a causal impact on household poverty, mainly through low wages. Yet other studies focus on the reverse causality from poverty to informality, arising from a range of constraints that poverty poses to job holders. Only recently have empirical researchers tried to study the simultaneous two-way relationship between poverty and informality. However, existing studies have relied upon cross sectional data and static econometric models.

This paper takes the next step and studies the dynamics of poverty and informality using longitudinal data. Our empirical analysis is based on a bivariate dynamic random effect probit model and recent panel data from Argentina. The results show that both poverty and informal employment are highly persistent processes at the individual level. Moreover, positive spillover effects are found from past poverty on current informal employment and from past informality to current poverty status, corroborating the view that the two processes are also shaped by interrelated dynamics.

1. Introduction

The persistence of high levels of informality and poverty in Argentina is a feature shared by many developing countries in the Latin American region. The nature of informality is a matter of controversy. Beyond its causes, it must be emphasized that informal jobs and poverty are connected. The fact that a large part of the informal workers are poor, and vice versa, supports this view. Poverty comprises those households below a certain income line. Informality, on the other side, includes a large fraction of workers with low earnings. Hence, low incomes appear as the link relating informality and poverty. Although there is some consensus around this asseveration there is still scarce evidence about the interactions between both phenomena.

The analysis of the relationship between poverty and informality allows disentangling the reasons that lead to certain individuals to engage in informal employment. Particularly, it will help to characterize whether the informality is the result of individuals' option –the supply-led view- or it is, instead, the consequence of the lack of opportunities for accessing to a formal job (demand-led view). The identification of poverty as one of the negative consequences caused by the informality is quite widespread in the literature. Informality may be one of the causes of poverty if informal jobs are associated with low incomes. When this occurs the probability of entering poverty for those households with members employed in the informal sector is higher. Consequently, an increase in informality –or a decrease in earnings from informal jobs- may be one of the sources of the growth of poverty. Therefore, an important bulk of the research has centered on the empirical evaluation of the existence of an earning gap between formality and informality. An issue still controversial in the studies about labor market segmentation. The reverse way may be considered as well. Household heads' earnings comprise a significant fraction of household incomes, but earnings contributions of other members, albeit from informal jobs, could decrease poverty.

Less explored is the inverse relationship. Indeed, the fact that a member of a poor household faces a greater chance to perform at an informal employment sustains a vision that emphasizes the involuntary nature of informality. The impossibility of getting a formal job (in a dual labor market well-paid jobs are scarce), usually with high and more stable incomes comparing to those from informal jobs, may lead to enter into informality.. This is regularly the only alternative to unemployment in the absence of generalized social security networks, a characteristic of Latin American countries. Restrictions to get formal jobs may arise due to certain factors associated with the condition of poverty (i.e. residential segregation, spatial labor mismatch, labor discrimination). Hence, informality would be the result of some poverty attributes.

The interconnection between informality and poverty can also be seen dynamically. In this case, having been employed in an informal job in the past may lead to poverty in the future. The sequence of events may be the following. Informal workers face high probabilities of losing their jobs because they are not protected by labor norms. When this happens, and during the period they stay as non-employed, the household's income decrease. They have little chances of getting a new job because they are not able to demonstrate past experience (employment is not documented under informality). Similarly, having suffered episodes of poverty may guide to episodes of informality hereafter. Low paid workers are usually low skilled and face a greater risk of being poor. If they lose their jobs, and assuming segmentation in the labor market, they will face difficulties to get back into a job. Informality may be the best alternative under these circumstances.

This document will contribute to the analyses about the interactions between informality and poverty providing evidence for the Argentinean case. We use panel data covering the period 1996-2003. The originality of this paper is not only the emphasis in the relationship between these phenomena from a static perspective but from a dynamic one. The question addressed here is if having an informal job/being poor at a given moment imply some probability of being poor/having an informal job in the near future. The focus will be in jobs of households'heads according to the relevance of their earnings in total income of the households. The paper is organized as follows. The next section describes previous research and section 3 the definitions and data used. Section 4 provides descriptive evidence about informality and poverty in Argentina. Section 5 presents the econometric approach. Section 6 analyses the results and section 7 other methodological issues. The conclusions are presented in section 8.

2. Previous research

Analyses of poverty dynamics are concerned with patterns and determinants of transitions and persistence. In general, results are that movements in and out of poverty are frequently associated with changes in employment status. On the other hand, several studies confirm the persistence of high rates of informal employment and poverty in Latin America (Perry et al., 2007; Worldbank, 2006). However, research about the connection between informality and poverty is insufficient. Gasparini and Tornaroli (2007) found that on average the difference in the poverty headcount ratio between informal and formal workers is around 4 times in the region. Amuedo-Dorantes (2004) using cross-section data for Chile concludes that household poverty increases the likelihood of employment in the informal sector. Also, it is shown that having an informal job raises the probability of becoming poor. Beccaria and Groisman (2008) explore if informality is the main cause of Argentinean poverty and find that the later one is not limited to households with members working in the informal sector.

There is a second group of research interests that is related to informality. As it was mentioned above, the analyses oriented to test the existence of segmented labor markets are close to this topic. The usual methodological approach consists on isolating the effect of informality from those derived from other income-determinants variables. Both parametric and semi-parametric methods can be found in various studies for different countries: Maloney (1999) for Mexico, Packard (2007) for Chile, Pratap and Quintin (2006) and Beccaria and Groisman (2008) for Argentina and World Bank (2007) for various Latin American countries. From a different methodological perspective Sosa Escudero and Arias (2008) analyze the interrelation between labor informality and relative informal/formal wages in Argentina. Although most of the papers find a formal premium, specially among wage earners, the reasons for being informal remain polemic.

From a methodological point of view, many approaches have been used to study the dynamics of poverty (Aassve et al., 2005). First, some papers have used components of variance models to capture the dynamics of income using a complex error structure (i.e. Lillard and Willis, 1978; Stevens, 1999 and Devicienti, 2001). These models are able to predict the fraction of population likely to be in poverty for different lengths of time. However, these models assume that the dynamics of the income process is identical for all individuals in the sample and this does not seem to match reality (Stevens, 1999; Devicienti, 2001).

Second, some other recent approximations to the estimation of outflow hazard rates propose the estimation of Markovian transition models (first order Markov) taking simultaneously into account that individuals are not randomly distributes either within the poor at first interview - initial conditions problem - or within the effectively observed at second interview - attrition problem –(i.e. Capellari and Jenkins, 2004). Alternatively, if first-order Markov assumption is violated, a long-standing approach to model poverty transitions has been the use of duration models in a hazard rate framework (i.e. Kalbfleisch and Prentice, 1980; Allison, 1982; Ducan, 1984; Bane and Ellwood, 1986; Jenkins, 1995; Devicienti, 2001; Hansen and Wahlberg, 2004; Biewen, 2006; Arranz and Canto, 2008).

Third, some more recent approaches to the analysis of poverty transitions chose to use binary dependent variable dynamic random effects models where the poverty situation at the moment t depends on the fact that you were poor at t-1, a list of covariates and some unobserved individual effects. In this case state dependence is summarized by the coefficient estimated for lagged poverty. In this type of models the distribution of the unobserved effect conditional on the initial value of poverty (initial conditions) and group of exogenous variables. See Wooldridge (2005) and, for examples of this approach to the analysis of poverty, see Poggi (2007) and Biewen (2008). Moreover, this type of models can be extended to analyse the relationship between two supposedly related concepts (i.e. poverty and informal employment). Devicienti and Poggi (2007) propose the use of a dynamic random effects bivariate probit following the recent contribution by Stewart (2007) who generalizes Wooldridge (2005) to the bivariate case.

3. Data

Data used in this document come from the household survey from Argentina (Permanent Household Survey –PHS– carried out by INDEC). Panel data is obtained from the rotating panel used to conform the sample of households interviewed. The survey covers urban areas and collects information on labour market variables, income and other social dimensions. Household and individual data are collected. Interviews are held two times a year (in May and in October). Households are visited in four successive moments or waves through a period of 18 months. Data for all urban areas are available from 1996. The questionnaires and methods of the PHS were modified in

2003. For that reason we focus on the period 1996 to 2003. Our unit of the analysis is the household head.

4. Informality and Poverty Trends

From mid-1970s to 1990 Argentina experienced a 15-year period of macroeconomic instability and productive stagnation. Gross domestic product (GDP) was broadly unchanged throughout that period and inflation remained at high levels. This process culminated in the hyperinflationary crisis of 1989 and 1990. In 1991 a stabilization programme based on economic openness was implemented and led to an increase in GDP. The Mexican crisis in late 1994 impacted on Argentina though the recession associated with this event was brief. From 1996 to 1998 the economy resumed a rapid growth path as soon as conditions on the international capital market improved. By the end of 1998, however, when this market became more problematic again and Brazil (a major export destination) went into recession, there was a new downswing in GDP. From 1999 to 2001 the economic difficulties increased markedly. Following the great crisis of 2001 the macroeconomic regime changed and inflation rose noticeably. Since 2002 Argentina experienced a steady and lasting economic recovery until 2008.

The serious macroeconomic instability experienced since the mid-1970s is one of the explanation for the significant deterioration in labor market with effects on wages, employment level and job quality, particularly for the lower skilled. Notwithstanding the difficulties that faced the Argentinean labor market during the nineties and the following decade –with unemployment levels around than 9% in 1993 and 16% in 2003– informality did not modify markedly its relative size. Instead, there was a marked advance in the share of non-registered salaried workers which entirely explains the expansion –modest in relation to labor difficulties – of informal employment. The main feature shown by occupational structure of the period was, then, the important advance of non--registered salaried workers (excluding domestic service and employment plans).

According to the International Labour Office, informality can be seen as the incapacity of economy to create enough jobs compared to the labour force. Thus, informal jobs are sometimes self-employment jobs and, in other cases, wage earners working in small units. According to this perspective, the informal unit is characterised by a no clear separation between capital and labour and usually acts in easy – entry activities and registers very low productivity. Alternatively, informality can be defined with the non compliance of labour regulations (mainly, evading taxes). However, the two definitions clearly overlap. In this paper, we combine both definitions (as it is usual in the literature): workers in informal employment are those in small firms (i.e. firm with less than five workers), those evading taxes (i.e. non-registered wage earners) and workers in domestic service.[1] The distinction between formal and informal employments refers to the main occupation (information about secondary employments are not available). About 51,7% of the household heads are employed in the informal sector in 2003. (see Table 1). During the period 1996-2003 informality incidence increased 2.7 p.p. on average. This aggregate performance combined an increase of non-registered wage earners and sharp decrease of registered workers in firms with more than five workers.

During the same period poverty increased dramatically.[2] Besides, informality rate among poor households was systematically higher indicating that those with informal jobs had lower probabilities of becoming non-poor. Similarly, poverty rate among the informal heads was also higher. From 1996 to 1998 overall poverty decreased although among informal households poverty incidence rose slightly. Poor households augmented markedly from 1998, both in informal and formal households.

Poverty and informality trends reflect different dynamics: informality showed greater stability than poverty during the period under analysis. Indeed, the latter rose sharply accompanying macroeconomic fluctuations. Secondly, the higher value of the rate of informal jobs (compared to that of poverty) anticipates that a significant proportion of the former correspond to non-poor households. Both pieces of evidence justify the research about interconnection of these phenomena.

Table 2 gives information about the sample composition showing differences in attributes between male and female household heads. The share of female heads is 17%.

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[1] Informal employment should also include those beneficiaries of employment plans. These plans were implemented by the government in the second half of the nineties and may be identified in the data since 2000. The universe under analyses is the group of households' heads at least once employed.

[2] We follow National Statistics and Census Institute's (INDEC) methodology for identifying poverty. It consists on computing the number of equivalent adults for each household and then computing a monetary poverty line also for each family. This approach accounts for households' composition

Women show an average age slightly larger than males' and run smaller households. The educational level was higher for women than for males while the hours worked and the employment rates were lower. The employment structure shows that male heads were highly concentrated in two categories: registered salary workers in firms with at least 6 employed people (44,6%) and non-wage earners in small firms (31,8%). Female heads also show high concentration in same categories than male but with high incidence of domestic service as well (23,9 %). Finally, the probability of working in the informal sector was really greater for women than for men, while the risk of falling below the poverty line was somewhat lower. Consequently, households headed by women showed higher rates of both poverty and informality.

5. Econometric model

Our aim is to analyze the relationship between two supposedly related concepts: poverty and informal employment. Following Devicienti and Poggi (2007), we introduce a dynamic random-effect bivariate probit model for the joint probability of experiencing the two states. The model allows for correlated unobserved heterogeneity and accounts for the initial conditions of the two processes. For an individual *i*, the risk of being in poverty at time *t* is expressed in terms of a latent variable y^*_{1it}, as specified as in equation (1), while the risk of working in the informal sector in *t* is expressed by the latent variable y^*_{2it}, specified in equation (2).

$$y^*_{1it} = x'_{it}\beta_1 + y_{1i,t-1}\gamma_{11} + y_{2i,t-1}\gamma_{12} + c_{1i} + u_{1it} \qquad (1)$$

$$y^*_{2it} = x'_{it}\beta_2 + y_{1i,t-1}\gamma_{21} + y_{2i,t-1}\gamma_{22} + c_{2i} + u_{2it} \qquad (2)$$

$$y_{jit} = 1\left[y^*_{jit} > 0\right], \qquad j = 1,2; \qquad t = 2, \ldots, T \qquad (3)$$

The dependent variables are the dummy indicators y_{1it} (equal to one if the individual is at risk of poverty in *t*, and zero otherwise) and y_{2it} (equal to one if individual *i* is employed in the informal sector in *t*, and zero otherwise). In the model represented by (1)-(3), x_{it} is a vector of independent variables, assumed to be strictly exogenous, and β=(β_1, β_2) is the corresponding vector of parameters to be estimated. The errors terms

according to sex and age. Total household income is compared to that line and poor households become

u_{1it} and u_{2it} are assumed to be independent over time and to follow a bivariate normal distribution, with zero means, unit variances and cross-equation covariance ρ. The model also includes individual random effects, c_{1i} and c_{2i}, assumed to be bivariate normal with variances σ_{c1}^2 and σ_{c2}^2 and covariance $\sigma_{c1}\,\sigma_{c2}\,\rho_c$. We also assume that ($c_{1i}$, c_{2i}), (u_{1it}, u_{2it}; t=1,…,T) and (x_{it}; t=1,…,T) are independent (implying that x_{it} is strictly exogenous). The dynamics of the model is here assumed to be first-order for simplicity.

This dynamic random-effects model is well suited to tackle the issue of "true state dependence" and to study dynamic spillover effects from poverty to informal employment and from informal employment to poverty. Therefore, we can establish the causal impact of past poverty on current poverty of past experiences in the informal sector on current probability of working in the informal sector, once the confounding impact due to unobserved heterogeneity is accounted for. To disentangle between unobserved heterogeneity and true state dependence, the lagged dependent variable, $y_{1i,t-1}$, is included in the poverty equation (1) and the lagged dependent variable $y_{2i,t-1}$ is included in the informal employment equation (2). Moreover, to take into account the spillover effects, the model also includes cross-effect lagged variables: lagged informal employment $y_{2i,t-1}$ is included in the poverty equation and lagged poverty $y_{1i,t-1}$ is included in the informal employment equation. This way it may be possible to understand whether the correlation observed in the data between, say, $y_{1,t-1}$ and y_{2t} is due to correlated unobserved heterogeneity (i.e., $\rho_c \neq 0$) or rather to state dependence across poverty and informal employment (i.e., the spillover effects γ_{12} and γ_{21} are non-zero).

The model is estimated following the approach proposed by Devicienti and Poggi (2007). They extended to the bivariate case the simple approach proposed by Wooldridge (2005) for univariate dynamic random effects probit models. Wooldridge (2005) proposes a Conditional Maximum Likelihood (CML) estimator that considers the distribution conditional on the initial values and the observed history of strictly exogenous explanatory variables. To generalize this approach in the context of our bivariate probit model, Devicienti and Poggi specify the individual specific effects

those with incomes below that value.

c_{i1} and c_{i2} given the initial conditions (y_{1i1} and y_{2i1}) and the time-constant explanatory variables $\bar{x}_i$, as follows:

$$c_{1i} = a_{10} + a_{11} y_{1i1} + a_{12} y_{2i1} + \bar{x}_i^{'} a_{13} + \alpha_{1i}$$
$$c_{2i} = a_{20} + a_{21} y_{1i1} + a_{22} y_{2i1} + \bar{x}_i^{'} a_{23} + \alpha_{2i}$$

where $a_{\mathrm{j}0}$, $a_{\mathrm{j}1}$, $a_{\mathrm{j}2}$ and $a_{\mathrm{j}3}$ (j=1,2) are parameters to be estimated, (α_{1i}, α_{2i}) are normally distributed with covariance matrix Σ_α:

$$\Sigma_\alpha = \begin{pmatrix} \sigma_{\alpha 1}^2 & \sigma_{\alpha 1}^2 \sigma_{\alpha 2}^2 \rho_\alpha \\ . & \sigma_{\alpha 2}^2 \end{pmatrix}.$$

Then after inserting in model (1)-(2) we obtain:

$$\begin{aligned} y_{1it}^{*} &= x_{it}^{'} \beta_1 + y_{1i,t-1}\gamma_{11} + y_{2i,t-1}\gamma_{12} + a_{10} + a_{11} y_{1i1} + a_{12} y_{2i1} + \bar{x}_i^{'} a_{13} + \alpha_{1i} + u_{1it} \\ y_{2it}^{*} &= x_{it}^{'} \beta_2 + y_{1i,t-1}\gamma_{21} + y_{2i,t-1}\gamma_{22} + a_{20} + a_{21} y_{1i1} + a_{22} y_{2i1} + \bar{x}_i^{'} a_{23} + \alpha_{2i} + u_{2it} \end{aligned} \quad (4)$$

Consistent estimates of the model's parameters can be obtained by Conditional Maximum Simulated Likelihood methods. The contribution of individual i to the likelihood may be written as follow:

$$L^W = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} \prod_{t=1}^{T} \Phi_2 \left(\tilde{y}_{1it}\mu_{1it}, \tilde{y}_{2it}\mu_{2it}, \tilde{y}_{1it}\tilde{y}_{2it}\rho \mid y_{1,t-1}, y_{2,t-1} \ldots x_{it}, \bar{x}_i \right) g\left(\alpha_1, \alpha_2, \Sigma_\alpha\right) d\alpha_{1i} d\alpha_{2i}$$

where μ_{1it} and μ_{2it} are the right-hand sides of equations in (4) excluding the error terms u_{1it} and u_{2it}.

Finally note that, according to Wooldridge (2005), the model need to be estimated on a balanced panel. Accordingly one may be worried that the estimator could potentially exacerbate attrition and sample selection present in the data. In fact, this is not the case, since Wooldridge's method has some advantages in facing selection and attrition problems. In particular, as explained in Wooldridge (2005; pp.44), it allows selection and attrition to depend on the initial conditions and, therefore, it allows attrition to differ across initial levels of deprivation. In particular, individuals with different initial statuses are allowed to have different missing data probabilities. Thus, we consider selection and attrition without explicitly modelling them as a function of the initial conditions. As a result, the analysis is less complicated and it compensates for the potential loss of information from using a balanced panel. Moreover, in the conditional MLE we can ignore any stratification that is a function of the initial level of deprivation and of the time-constant explanatory variables: thus, using sampling weights would lead to an efficiency loss.

6. Results

In this section, we present the estimates of the dynamic model for poverty and informality discussed in the previous section. In order to make the interpretation of the results easier, standard bivariate probit estimates are also presented. The unit of the analysis is the household head. Results for male and female household heads are presented separately. See Tables 3-4. Covariates included in the vector x_{it} refer to individual-level characteristics: gender, age (linear), dummies for high and medium education (low education is the reference category), marital status (=1 if married) and job attributes as tenure (linear), occupation (blue or white collars), sector dummies, area dummies and firm-size. These variables are treated as time-constant variables.[3] Household-level characteristics are also included in x_{it}: the number of the household members and the number of working members of the household. Only the latter varies over our period of analysis (thus, in the specification of the dynamic random effects model we also include the corresponding time-average variable in order to allow for correlation between the individual specific effects and the time varying variable). A set of period dummies is also included in the specification to capture the macroeconomic environment. In both equations, the same explanatory variables are used. While in principle a wider set of influences may be considered, we have maintained our reduced-form specifications relatively parsimonious because (i) we are already controlling for (correlated) unobserved heterogeneity, (ii) the estimation of our model is already computationally demanding. More importantly, the variables included in x_{it} do not constitute the main focus of the analysis: this lies instead in the interrelated dynamics of

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[3] We observe no variability over the period of study (i.e. marital status) or very limited variability, so we decide to treat these variables as time constant to simplify the specification since the estimation of our model is already computationally demanding.

poverty and informal sector employment, which is reflected in the estimates of the lagged indicators for both dependent variables

The joint estimation of the model equations is necessary: ρ is positive and statistically significant in all the specifications (both for male and female household heads). Therefore, the myriad of idiosyncratic shocks that, at any given time period, drive people into poverty and into informal sector employment have common elements. The estimates of the pooled bivariate probit models do not control for individual unobserved heterogeneity and assumes that the initial conditions are exogenous. One would then expect that this estimator overestimate the importance of state dependence, as the coefficient of the lagged dependent variable absorbs part of the effect that is instead due to (uncontrolled) unobserved heterogeneity. A quick glance at Tables 3-4 confirms that this is indeed the case. Therefore, the random effects bivariate probit model has to be preferred to the standard bivariate model.

Male Household Heads: random effect bivariate probit model

Estimates for male household heads are reported in Table 3. For poverty, after controlling for unobserved heterogeneity, the lag coefficient is still statistically significant and it is estimated at 0.3; the lag cross effect is also sizeable: it is estimated at 0.2 in the poverty equation. For informal sector employment, own lag estimate is even higher, at 0.6, and the lag cross-effect is estimated at 0.1.

In both equations the initial values are also very important, and this implies that there is substantial correlation between the initial condition and the unobserved heterogeneity. For poverty, the coefficient on initial poverty (1.4) is much larger that the coefficient on the lag (0.3), while the coefficient on initial informal sector employment is statistically not different from the coefficient on the cross-lag (0.2). For informal sector employment, the coefficient on initial informal sector employment (3.05) is much larger than the coefficient on the lag (0.6); the coefficient on initial poverty (0.2) is also larger than the coefficient on the cross-lag (0.1).

The standard deviations of the random effects are statistically significant and positive for both poverty and informal sector employment. This means that unobserved heterogeneity plays a role in explaining the observed persistence in poverty and informal sector employment.

High values of coefficients (of initial condition and on the lag event) in the informality equation reveal the segmented nature of labor market. These figures show that probabilities of leaving informality are very low for male heads. Instead, the values of similar coefficients in poverty equation may be interpreted as indicative of a more flexible pattern. This is an expected evolution since poverty transitions in the short run usually derive from income changes that are closely related to macroeconomic fluctuations. We have already mentioned that the informality rate showed great stability all along the period while the incidence of poverty fluctuated according to the economic performance. Consequently the observed cross-lag effects were of low intensity although robust.

Individuals with high-medium education have a lower risk of being in poverty than those with low education. Age, entered linearly for simplicity, has a small negative and statistically significant effect on income poverty, reflecting the increased command on economic resources as the individual ages. However, age has an opposite effects on informal sector employment indicating that older workers have more possibilities of working in the informal sector than younger workers. This is consistent with two complementary hypotheses. Firstly, firms would prefer to register younger workers. Secondly, older people would exhibit a larger entrepreneurial spirit that younger workers. The number of working members in the household decreases the probability of being in poverty, while the average number of working members increases the probabilities of working in the informal sector. A possible explanation for this correlation is the presence of barriers that limit access to formal jobs for spouses and other members. It may reflect also strong social networks in the informal sphere. Conversely, the risk of poverty increases with the number of the household members. Blue collar workers have higher probabilities of being poor than white collar workers, while workers with long tenure have low probabilities of being poor. Individuals working in small firms have both high probabilities of being poor and being employed in the informal sector. This is a common feature of Latin American labor markets where small firms tend to have low productivity and concentrate a great proportion of non-registered workers. Finally, differences in the probabilities of being poor and/or employed in the informal sector are observed across individuals working in different sectors and different regions.

Female Household Heads: dynamic bivariate random effect model

Estimates for female household heads are reported in Table 4. For poverty, after controlling for unobserved heterogeneity, the lag coefficient is estimated at 0.4 and the lag cross effect is estimated at 0.6. For informal sector employment, own lag estimate is at 0.8, and the lag cross-effect is estimated at 0.4. In both equations, the coefficients on the lag and the cross-lag are larger than the ones observed in Table 3 for male household heads.

In both equations the initial values are, once again, very important pointing to the existence of substantial correlation between the initial condition and the unobserved heterogeneity. For poverty, the coefficient on initial poverty is estimated at 1.2 and the coefficient on initial informal sector employment is estimated at 0.3. For informal sector employment, the coefficient on initial informal sector employment is estimated at 2.8 and the coefficient on initial poverty (0.5). Thus, we find some evidence that cross-lag effects are stronger for female household heads than for males. High concentration of female heads in domestic service may be part of the explanation. It must be emphasized that this activity has low barriers to entry/exit and low monthly income. In the same direction the fact that female heads (usually in charge of little children) face low opportunities of getting high-quality jobs (i.e. more stable) might also influence this stronger relationship.

The standard deviations of the random effects are statistically significant and positive for both poverty and informal sector employment. However, unobserved heterogeneity seems to play a slightly smaller role in explaining the observed persistence in poverty and informal sector employment for female household heads than for male household heads. In facts, in both equations, the standard deviations result to be slightly smaller for female household heads than for male household heads.

Individuals with high-medium education have a lower risk of being in poverty than those with low education. Unexpected, age does not have a significant effect on poverty. The number of working members in the household decreases the probability of being in poverty, while the average number of working members increases the probabilities of working in the informal sector (one again point in the direction of presence of barriers that limit access to a formal jobs and/or the existence of strong social networks). Conversely, the risk of poverty increases with the number of the household members. There are no significant differences in the probabilities of being poor between blue and white collar workers, and between female workers in small or large sized firms. But, females working in small firms have high probabilities of being employed in the informal sector. Workers with long tenure have low probabilities of being poor, while employment in informal sector is associated with shorter tenures than employment in the formal sector. Finally, differences in the probabilities of being poor and/or employed in the informal sector are observed across females working in different sectors and different regions.

Predicted probabilities: male versus female probabilities

For both equations, the lagged dependent variables concerning poverty and informal sector employment are significantly positive. To evaluate the relevance of the dynamics in the model, we estimate the predicted probabilities of being in poverty, and for working in the informal sector, for various lagged statuses of poverty-informal sector employment (Table 5). As suggested by Wooldridge (2005), predicted probabilities are first computed at individual characteristics, keeping lagged dependent variables at specified values, and then averaged in the sample. The estimated parameters corresponding to each variable in $X_{it}=(x_{it}, y_{1i,t-1}, y_{2i,t-1}, y_{1jit-2}, y_{2jit-2})$ are multiplied by $\left(1+\hat{\sigma}_j^2\right)^{-1/2}$, for j=1,2, so as take into account the estimated distribution of unobserved heterogeneity, and the corresponding linear predictions are inserted into the cumulative standard normal distribution function, separately for each equation.

For male household heads, the probability of being poor in t is about 0.25 for those who were non-poor and not-employed in the informal sector in t-1. This probability increases to 0.18 for female household workers. However, the same probability is larger, at 0.23, if the female household head was poor the year before, albeit not employed in the informal sector. The probability is 0.29 if we look to male household heads poor the year before if not-employed in the informal sector. For females and males, both poor and employed in the informal sector in *t*-1, the chances of being poor in *t* raise further, at about 0.32.

For male and female household heads, the probabilities of working in the informal sector are about 0.42, if the household head was non-poor and not-employed in the informal sector in *t*-1. These probabilities are higher (respectively, at 0.495 and 0.509), if the household head was employed in the informal sector the year before, albeit not poor. For those both poor and employed in the informal sector in *t*-1, the chances of working in the informal sector in *t* slightly increase, respectively, at about 0.507 and 0.551.

These results are compatible with the presence of barriers along the informal/formal line in labor market. In contrast, past episodes of poverty did not have similar effects (on future events) in the case of households ruled by male heads. This suggests that income fluctuations of households located above / below the poverty line were widespread. Female heads, instead, showed positive effects from past poverty episodes. Cross-lag effects from poverty to informality were observed and give support to the hypothesis of informality as non-voluntary (as an alternative to unemployment). In contrast, informal cross-lag effects were obtained only for households headed by women in line with the explanation already mentioned about the higher difficulties they face in labor market.

7. Sample selection issues

In this section, we discuss the impact of eventual sample selection problems deriving from the fact that the model is estimated only on wage and salary workers. The male population (aged 16-65) is composed as following: 81.42% employed, 7.92% unemployed and 10.66% inactive men (7.25% retired, 0.3% renter, 0.87% student; 0.65% disables, 1.59% others). The female population (aged 16-65) is composed as following: 56.71% employed, 6.43% unemployed and 36.86% inactive women (18.79% retired, 0.92% renter, 2.78% student; 13.67% housewife, 0.31% disables, 0.39% others). To correct for any selection bias in moving from the entire population to the working individuals, we compute a Mills ratio using a selection variables that equals 1 at period t if the individual is observed over the entire period of analysis and works in period t (Clark and Etilé, 2006). We estimated selection equations separately on the male and female populations, as function of age, education, a dummy variable indicating whether the respondent is attending school, marital status, household size, number of working household members, number of children younger than 6 years old, regional dummies and period dummies. The selection equations are identified by the exclusion of the dummy variable indicating whether the respondent is attending school and by the exclusion of the number of children under the age of 6 in the household from the structural equations (similar instruments have been previous used by Amuedo-Dorantes, 2004). Both of these variables are not significant in the structural equations once we account for the worker's skill through occupation dummies and for family size. Results from selection regressions and from the random effect bivariate model are available on request. Table 5 shows the predicted probabilities of being in poverty, and for working in the informal sector, for various lagged statuses of poverty-informal sector employment. Results are robust with the ones presented above

8. Conclusions

In this paper we have studied the determinants of poverty and informal employment using recent panel data from Argentina. In particular we aimed at uncovering a mutually causal relationship between household poverty and household heads' employment in the informal sector, a relationship that has attracted the interest of both academic researchers and policy makers.

A notable contribution in this area is the study of Amuendo-Dorantes (2004), who estimates simultaneous probit equations for poverty and informal employment. While her analysis provides important insights on the way the two processes are jointly determined, a potential limitation lies in her reliance on cross sectional data and static econometric models. The model identification than crucially depends upon a number of exclusion restrictions that, while holding in her study, are not guaranteed to hold in other cases, preventing further investigations of the same issues.

In this paper we have pursued an alternative approach based on panel data and a dynamic bivariate probit model with random effects. The identification strategy relies upon the observed *changes* in an individual status of poverty and informal employment, which is convenient to our aims given that the types of exclusion restrictions used by Amuendo-Dorantes did not hold in our case. Our model provides a means of assessing the persistence over time of poverty and informal employment at the individual level, while controlling for both observed and unobserved determinants of the two processes. Moreover, the model accommodates the potential existence of spillover effects from past poverty to current informality status and from past informality to current poverty status. These dynamic spillover effects might be crucial determinants of the persistence of both poverty and informality that have not been previously studied in the literature.

Our results from Argentina show that indeed poverty and informal employment are highly persistent processes at the individual level. Moreover, statistically significant and positive spillover effects are found running both from past poverty to current informal employment and from past informality to current poverty status, corroborating the view that the two processes are also shaped by interrelated dynamics.

Finally, both phenomena, although overlapped in many cases, involve diverse groups and show different dynamics. Poverty appears to respond more to income fluctuations and less to the informal characteristics of jobs. Our results also reveal differences between male and female heads.

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Table 1. Employment Structure and Poverty: all urban areas

% heads of households	May-96	Oct-98	Oct-01	May-03
Formal Employment				
Non-wage earners (firm size >5)	2.0	1.6	1.6	1.1
Registered wage earners (firm size >5)	42.1	40.5	38.9	34.0
Registered wage earners (firm size <=5)	6.8	6.3	6.0	5.5
Informal Employment				
Non-wage earners (firm size <=5)	30.2	29.1	30.2	29.4
Non-registered wage earners (firm size >5)	6.9	9.3	7.8	8.6
Non-registered wage earners (firm size <=5)	7.4	8.6	9.2	8.4
Domestic service	4.5	4.8	4.8	5.2
Employment Plans			1.5	7.7
Informal Employment *(1)*				
Overall	49	51.7	52	51.7
Poor households	62.5	70.1	71.6	69.9
Absolute Poverty incidence				
Overall	22.1	21.8	28.3	42.8
Head of Household informal	25	27.2	35.8	54.9

(1) Excluding Employment Plans

Table 2. Sample composition: all urban areas

Heads of households (ever employed)	Female	Male	Total
Sex (%)	17	83	100
Age (mean)	47	44	44
Household Size	2,9	4,1	3,9
Education (%)			
Low	60	65	64
Medium	25	26	26
High	14	10	10
Total	100	100	100
Employment rate (%)	79,8	89,6	87,9
Hours worked a week (mean)	33	44	43
Employment Structure (Obs. 1) (%)			
Formal Employment			
Non-wage earners (firm size >5)	0,5	1,9	1,7
Registered wage earners (firm size >5)	39,0	44,6	43,7
Registered wage earners (firm size <=5)	5,2	6,2	6,1
Informal employment (1)			
Non-wage earners (firm size <=5)	19,4	31,8	29,9
Non-registered wage earners (firm size >5)	6,5	7,7	7,5
Non-registered wage earners (firm size <=5)	5,6	7,4	7,1
Domestic service	23,9	0,5	4,1
Informal Employment (%)			
Obs 1	55,4	47,3	48,6
Obs 2	54,8	47,5	48,6
Obs 3	55,1	48,0	49,1
Obs 4	55,6	48,5	49,6
Poverty Incidence (%)			
Obs 1	29,5	30,1	30,0
Obs 2	31,2	32,5	32,3
Obs 3	32,6	34,0	33,7
Obs 4	32,7	34,8	34,4
Both Informal and Poor (%)			
Obs 1	15,6	14,1	14,4
Obs 2	15,8	14,9	15,1
Obs 3	17,9	15,9	16,2
Obs 4	17,4	16,5	16,7
N	4844	23621	28465

(1) Employment plans are included in the category "Non-registered wage earners".

Table 3. Male household heads: estimates

(only male head households)	Poverty Coef		Poverty Robust SE	Informality Coef		Informality Robust SE	Poverty Coef		Poverty Robust SE	Informality Coef		Informality Robust SE
Lpoor	1.3257	**	0.0269	0.1700	**	0.0284	**0.3446**	**	**0.0472**	**0.1088**	*	**0.0670**
Linformal	0.2896	**	0.0286	2.1882	**	0.0299	**0.2074**	**	**0.0748**	**0.5859**	**	**0.0634**
poor0	**No**		**No**	**No**		**No**	**1.4299**	**	**0.0658**	**0.2150**	**	**0.0737**
infom0	**No**		**No**	**No**		**No**	**0.2031**	**	**0.0783**	**3.0479**	**	**0.1438**
Age	-0.0022		0.0012	0.0068	**	0.0012	-0.0042	**	0.0020	0.0108	**	0.0026
Married	-0.0198		0.0551	-0.0476		0.0475	-0.0153		0.0849	-0.0619		0.1018
Hsize	0.2703	**	0.0079	-0.0106		0.0069	0.3790	**	0.0146	-0.0199		0.0155
hsize_work	-0.5872	**	0.0183	0.0552	**	0.0152	-0.8814	**	0.0404	0.0234		0.0472
high_edu0	-0.9426	**	0.0607	0.1013	*	0.0393	-1.3405	**	0.0925	0.1419		0.0810
Medium_edu0	-0.5201	**	0.0264	-0.0034		0.0242	-0.7221	**	0.0450	-0.0268		0.0538
Tenure	-0.0009	**	0.0001	-0.0007	**	0.0001	-0.0012	**	0.0002	-0.0009	**	0.0002
blue_collar0	0.1194	**	0.0312	0.0778	*	0.0307	0.1978	**	0.0531	0.0741		0.0677
_Isector0_3	0.2552	**	0.0343	0.3153	**	0.0366	0.3378	**	0.0580	0.5227	**	0.0805
_Isector0_7	0.0764	*	0.0375	0.0725	*	0.0351	0.1144	*	0.0624	0.1063		0.0792
_Isector0_8	-0.0908	*	0.0429	0.1764	**	0.0402	-0.1071		0.0729	0.2913	**	0.0904
_Isector0_9	0.0883		0.0486	-0.0690		0.0436	0.1483	*	0.0820	-0.2617	**	0.1000
_Isector0_10	0.1042	**	0.0392	-0.4216	**	0.0407	0.1458	**	0.0660	-0.7279	**	0.0905
_Isector0_11	-0.1349	*	0.0573	-0.0475		0.0465	-0.2259	**	0.0968	-0.1503		0.1035
small0	0.1030	**	0.0285	0.6832	**	0.0236	0.1383	**	0.0504	0.7928	**	0.0646
_Iarea0_2-	0.1422	**	0.0342	0.0360		0.0311	0.1688	**	0.0572	0.1020		0.0695
_Iarea0_3-	0.3066	**	0.0395	-0.0006		0.0372	0.3987	**	0.0653	-0.0470		0.0820
_Iarea0_4-	0.4493	**	0.0352	0.0911	**	0.0342	0.6168	**	0.0599	0.1271	*	0.0748
_Iarea0_5-	-0.1990	**	0.0412	-0.0746	*	0.0357	-0.3075	**	0.0667	-0.1032		0.0792
_Iarea0_6	0.5651	**	0.0395	0.1001	*	0.0400	0.7826	**	0.0688	0.1863	**	0.0877
Period dummies	**yes**		**yes**	**yes**		**yes**	**yes**		**yes**	**yes**		**yes**
m_hsize_work	**no**		**No**	**no**		**no**	0.0548		0.0492	0.0980	*	0.0603
_cons	-1.6071	**	0.0941	-1.7895	**	0.0899	-2.1600	**	0.1465	-2.8160	**	0.1887
Rho				0.1673	**	0.0195				0.2081	**	0.0417
log-pseudolikelihood						-17440.26						-16532.65
No. Obs						29763						29763
No. Clusters						9921						9921
sig_a1										1.3319	**	0.0634
sig_a2										0.9664	**	0.0414
r_a										0.1467	**	0.0474

Table 4. Female household heads: estimates

(only female head households)	Poverty Coef		Poverty Robust SE	Informality Coef		Informality Robust SE	Poverty Coef		Poverty Robust SE	Informality Coef		Informality Robust SE
Lpoor	**1.279**	**	**0.064**	**0.407**	**	**0.083**	**0.4248**	**	**0.1105**	**0.4284**	**	**0.1818**
Linformal	**0.653**	**	**0.083**	**2.397**	**	**0.082**	**0.6033**	**	**0.2094**	**0.8679**	**	**0.1803**
poor0	**no**		**No**	**no**		**no**	**1.2271**	**	**0.1467**	**0.5281**	**	**0.2085**
infom0	**no**		**No**	**no**		**no**	**0.2754**		**0.2186**	**2.8748**	**	**0.4142**
Age	-0.004		0.003	0.007	*	0.003	-0.0052		0.0047	0.0128	*	0.0065
Married	-0.011		0.064	-0.030		0.066	-0.0480		0.1014	-0.0027		0.1391
Hsize	0.346	**	0.022	-0.055	**	0.020	0.4767	**	0.0410	-0.1467	**	0.0469
hsize_work	-0.700	**	0.052	0.103	*	0.051	-1.0570	**	0.1098	-0.1800		0.1422
high_edu0	-0.762	**	0.108	0.035		0.087	-1.0717	**	0.1607	0.0919		0.1688
Medium_edu0	-0.464	**	0.067	-0.241	**	0.067	-0.7544	**	0.1141	-0.3951	**	0.1430
Tenure	-0.001	*	0.000	-0.001	**	0.000	-0.0011	**	0.0005	-0.0020	**	0.0007
blue_collar0	-0.038		0.160	0.232		0.143	0.0206		0.2693	0.2100		0.3441
_Isector0_3	-0.209		0.440	0.053		0.575	-0.2299		0.5477	0.1317		0.8350
_Isector0_7	-0.156		0.151	0.216		0.128	-0.1439		0.2411	0.1551		0.2910
_Isector0_8	-0.381		0.232	-0.079		0.234	-0.3755		0.4038	-0.1026		0.4297
_Isector0_9	-0.363		0.157	-0.262		0.133	-0.4778	*	0.2589	-0.7262	**	0.3107
_Isector0_10	-0.069		0.148	-0.462	**	0.131	-0.0701		0.2496	-0.8639	**	0.3051
_Isector0_11	-0.230		0.205	-0.319	*	0.156	-0.3104		0.3096	-0.6723	*	0.3439
small0	0.009		0.089	0.685	**	0.068	-0.0782		0.1410	0.9602	**	0.1807
_Iarea0_2-	0.304	**	0.098	-0.228	**	0.082	0.4464	**	0.1488	-0.3909	**	0.1766
_Iarea0_3-	0.387	**	0.110	-0.169		0.107	0.6159	**	0.1750	-0.2193		0.2146
_Iarea0_4-	0.477	**	0.098	-0.145		0.090	0.6812	**	0.1528	-0.3341	*	0.1915
_Iarea0_5-	-0.161		0.111	-0.400	**	0.091	-0.2408		0.1654	-0.6037	**	0.2072
_Iarea0_6	0.619	**	0.106	-0.104		0.105	0.8567	**	0.1731	-0.1776		0.2341
Period dummies	**yes**		**yes**	**yes**		**yes**	**yes**		**yes**	**yes**		**yes**
m_hsize_work	**no**		**No**	**no**		**no**	0.1000		0.1342	0.5380	**	0.1829
_cons	-1.287	**	0.228	-1.444	**	0.252	-1.7797	**	0.3811	-2.3376	**	0.4748
Rho				0.331	**	0.053				0.4957	**	0.1309
log-pseudolikelihood						-2673.21						-2539.27
No. Obs						5718						5718
No. Clusters						1906						1906
sig_a1										1.2198	**	0.1803
sig_a2										0.8911	**	0.0958
r_a										0.1660		0.1290

Table 5. Probabilities **Probability of status in t-1**		**Probability of status in t**											
		Pooled bivariate probit model				Random-effect bivariate probit model				Random-effect bivariate probit model with IV			
t-1		**Males**		**Female**		**Males**		**Female**		**Males**		**Female**	
Poor	Informal sector	Poor	Informal sector	Poor	Informal sector	Poor	Informal sector	Poor	Informal sector	Poor	Informal sector	Poor	Informal sector
0	0	0.145	0.138	0.0957	0.1299	0.24836	0.42711	0.1787	0.4248	0.24543	0.42696	0.17723	0.42276
1	0	0.475	0.173	0.3584	0.2151	0.29644	0.4396	0.2308	0.4662	0.29546	0.44273	0.25123	0.45188
0	1	0.2	0.802	0.203	0.7942	0.2767	0.4946	0.2554	0.5085	0.27833	0.49494	0.23077	0.50726
1	1	0.562	0.844	0.555	0.8765	0.32775	0.5073	0.3205	0.5513	0.33197	0.51099	0.31789	0.53704