Is There a Poverty Trap in Paraguay? Evidence from Pseudo-panels and Nonlinear Income Dynamics

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Abstract

In this study we examine the existence of income poverty traps in Paraguay's urban and rural areas. In order to do so, we use dynamic pseudo panels to overcome difficulties that arise with traditional panels: lack of long panels in developing countries, measurement errors and attrition. For rural areas, we find non linear income dynamics, but no evidence of poverty traps, even allowing for cohort heterogeneity. On the other hand, our outcomes for urban areas vary between models, as we find that under some specifications there is an unstable equilibrium indicating there could be a trap affecting households that fall under a critical threshold, although this threshold is below the data range for urban income.

Key words: poverty trap, pseudo panels, income dynamics. Palabras clave: trampa de pobreza, pseudo paneles, dinámicas de ingreso.

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1 Introduction

A poverty trap is present when future poverty is caused by current poverty. This means that certain groups of individuals are condemned to experience reduced income mobility, or no mobility at all, and cannot escape their condition of poverty. Traps do not include individuals that are poor a few moments in time, but rather those who stay poor because they are unable to get out of the situation. This goes against the belief that hard work and determination will get you where you want to go. It is important to detect the existence of this trap because it provides an explanation for the persistence of poverty and it is the first step to design appropriate policies.

In this investigation, we use household survey data from Paraguay to create pseudo panels and employ them to estimate non-linear income dynamics in an attempt to empirically detect or discard the existence of a poverty trap in income, discriminating by rural and urban areas.

2 Motivation

Poverty has become one of the most significant global concerns in today's world. The first goal in the United Nation's Sustainable Development Goals (SDGs) is "eradicating extreme poverty for all people everywhere by 2030" (United Nations, 2024). However, the United Nations has also warned that, if current patterns continue, 575 million people will still be under extreme poverty by then. Therefore, the goal of eradicating poverty has become an ambitious one, and requires thorough research on the most appropriate policies.

An idea that has been sustained for years is that economic growth and the redistribution of resources, either through the government or through foreign aid, is a suitable strategy to fight poverty. However, Page & Pande (2018) argue that these historical ideas will not be sufficient to end poverty by 2030. They instead propose that states in poor countries should be strengthened and take up responsibility for the necessities of the most vulnerable. They claim that foreign aid could be useful if it helps build up domestic institutions, rather than weaken them.

In the presence of a poverty trap, a relevant policy is transfers to create jobs for the poor. Balboni et al (2022) claim that one possible reason why the poor stay poor is that poverty traps exist, and it is a person's initial wealth what traps them into hardship, not their abilities. An opposite perspective is that the poor remain in precarious circumstances because, even if they have the same opportunities as everyone else, they do not have the necessary abilities to acquire a higher income job. The authors try to test these views empirically. They employ a randomized asset transfer and a panel that covers a total of 11 years and 6,000 households that begin in extreme poverty. They do this for rural Bangladesh, where the assets in question are cows, and find that the data supports the existence of a poverty trap. Consequently, they argue that transfers could have large effects and contribute in reducing global poverty.

Therefore, the detection of a poverty trap has important implications for the development of policy and acts as a call to action. Some traps are described with single stable states that appear because of an immutable condition that is specific to households (Barrett & Carter, 2013). There are also multiple equilibrium poverty traps, where there is one or more equilibria associated with poverty. This would mean that "a different equilibrium is possible and also that one-time policy efforts that break the poverty trap may have lasting effects" (Kraay & McKenzie, 2014, p.127). These traps are sometimes used as the justification for increasing amounts of foreign aid to developing countries. This is because it is believed that it would act as the necessary big push to exit the trap and enter a virtuous cycle.

Kraay & McKenzie (2014) also explain that a poverty trap at a national level is related or based on the existence of traps at a household level. So poverty traps not only provide a basis for the use of foreign aid but also justify the use of microfinance loans to try to allow households to break out of poverty. However, the impact of different policies depends on the type of trap that is present, that is, on the mechanism behind it (Barrett & Carter, 2013). For example, foreign aid and loans would be useful if the trap occurs because countries cannot afford to save and a way to finance investment is needed. A report by the United Nations Conference on Trade and Development states that increased aid to Africa could act as a big push to start "a virtuous circle of higher rates of savings, investment and economic growth (...) necessary for a permanent reduction in poverty" (UNCTAD, 2006).

Sometimes, less traditional actions are more appropriate. Kraay & McKenzie (2014) find that promoting migration could be beneficial if the trap is geographical. Nevertheless, the detection of a poverty trap by itself is an important step for policy making and provides powerful insight on the income mobility of a country. Our work does not evaluate the mechanism behind a trap, but rather aims to detect or discard its existence using household data. This is the first work to do so for the country of Paraguay utilizing estimations of non-lineal income dynamics and pseudo panels, following Antman & McKenzie (2007a).

2.1 Paraguay

Paraguay is a landlocked country situated in Latin America. For decades, poverty remains a top concern for the region, as many still lack stable access to education, health, housing and sanitation (Gasparini et al, 2021). Currently, the country has a population of 6,700,000 people, of which 2.800.000 live in the capital city of Asunción (Enciclopedia Humanidades, 2025), indicating accelerating urbanization. Its economy is heavily dependent on agriculture, especially soybeans.

During the 90s, Paraguay suffered from political instability, internal conflicts and institutional crises. In 2003, the poverty rate was 51.4%, meaning more than half of the population lacked the resources to meet essential living needs. At the start of the century, it experienced low economic growth compared to other countries in the region (Cruces et al, 2017). Further-

more, it suffered greatly from the 2008 crisis and went through another recession in 2012 due to a severe drought. Nonetheless, in recent years, strong macroeconomic policy has allowed for certain growth (World Bank, 2025). This also helped in improving the living conditions and, therefore, lowering the poverty rate. In 2022, Paraguay's poverty rate was 24.7%, aligning with the regional average. This is a drastic decrease since 2003. However, it still means that almost 1 in every 4 people are poor. In addition, as of 2024 it was revealed that 28.3% of the population lack access to at least one basic need, as stated by the director of Paraguay's national institute of statistics (INE) (TeleSUR, 2024).

The country continues to be in a vulnerable position as the rate of reduction of poverty has slowed down over the last years, with most of the progress on this matter occurring between 2003 and 2013 (World Bank Document, 2024). There also appear to be elevated levels of inequality, with a Gini coefficient of 45, higher than that of Albania, Armenia and Túnez (World Bank Document, 2024). This leads to the fact that "significant challenges persist in terms of inequality and vulnerability to external shocks, underscoring the need for strategic actions to maintain and accelerate the progress achieved" (Banco Mundial, 2024). According to the World Bank, some factors that obstruct Paraguay's ability to reduce poverty are: "large gaps in human capital accumulation, limited creation of and access to quality jobs, a fiscal system with a modest impact on poverty reduction, and climate-related risks" (World Bank, 2025). The country remains at risk of external climatic shocks due to its reliance on agriculture (World Bank, 2025). It also faces the problem of alarming child poverty. In 2024, Unicef reported that 37.6% of children in Paraguay lived under the basic needs line. All of these observations add complexity to the issue and highlight the importance of studying poverty in the territory.

In 2023, the National Institute of Statistics of Paraguay (INE) set the monthly poverty threshold for a person at 853,778 guaraníes (107.23 US dollars) in urban areas and 618,789 guaraníes (77.72 US dollars) in rural areas. For extreme poverty, the values were 359,480 and 328,289 guaraníes, respectively (45.15 and 41.23 US dollars). For our investigation, values were deflated using the country's official CPI and 2010 as the base year, so the relevant poverty lines are 493,061 guaraníes (107.77 2010 US dollars) for urban areas and 352,073 guaraníes (76.95 2010 US dollars) for rural areas. The values for extreme poverty would be 187,637 (40.1 2010 US dollars) and 171,357 guaraníes (37.46 2010 US dollars), respectively.

3 Literature on income mobility and poverty traps

Literature on poverty traps can be divided into two groups. The first group uses models, both at macro and micro levels, to try to explain the mechanisms through which a trap is created. These models provide a basis for the existence of non-linear income dynamics in household's accumulation of income or assets. A poverty trap implies that income dynamics are very different for those who initially have higher incomes and those who are initially poor (Kraay & McKenzie, 2014). Therefore, another group of literature studies these dynamics directly and conjointly tests all the model's hypothesis empirically. Poverty traps appear as equilibriums below a specific threshold in income, assets or expenditure, that households are unable to surpass. Our work belongs to this second group of literature, particularly with papers that analyze income dynamics with parametric tactics.

Inside the first group, the most used macro mechanisms are savings and coordination failure and the most well-known for micro are nutrition and lumpy investments, referring to large and indivisible investments (Kraay & McKenzie, 2014). There are also behavioral and geographical poverty traps. Some mechanisms operate at a household level, while others function in a broader scope, such as a regional or even national level (Barrett & Carter, 2013).

The savings mechanism argues that if individuals cannot save up money because they are too poor, they are unable to accumulate capital and so their income will become stagnant if there is no growth in total factor productivity (Kraay & McKenzie, 2014). With regard to coordination failure, a well known theory is that of Rosenstein-Rodan (1943) known as the "big push". Murphy, Shleifer and Vishny (1989) elaborate on the idea and explain that small domestic markets may be stuck in a no-industrialization trap. Coordination problems between firms may leave the economy at a lower standard of living that the one which could be achieved if the different sectors were to simultaneously industrialize and enjoy spillover effects. The big push in this case is associated with multiple equilibria, going from a cottage production equilibrium to an industrial one. Thus, encouraging simultaneous industrialization can be profitable.

Among the micro mechanisms, Dasgupta & Ray (1986) link unemployment with malnutrition. In their model, individuals who have income from assets can acquire a proper nutrition while others cannot. With not enough nutrients, workers cannot be productive at work, and therefore do not earn enough to buy nourishment. Some may be involuntarily unemployed and malnourished because the market cannot afford to employ them all. The idea behind this is that there are increasing returns to scale in the food-productivity relation of an individual who has low levels of consumption. However, Kraay & McKenzie (2014) state that, although there is room for policy efforts in nutrition, a poverty trap of this manner is unlikely. They argue that calories can be cheap in most of the undeveloped countries and that the shape of the relationship is not the S-shaped needed for poverty trap dynamics.

As for investment, Banerjee & Newman (1993) focus on the interaction between an individual's distribution of wealth and his occupational decisions. Agents must choose between working for a wage or self-employment, but entrepreneurial activity requires certain capital for investment. The entrepreneurs then become the wealthy agents that supervise the others and the salary men may be trapped and never be able to invest. This is related to capital market imperfections, as individuals are restricted to how much they can borrow, and to non convex technology (investing a low amount has low returns, investing much more has higher returns).

Ceroni (2003) focuses on human capital accumulation as a mechanism that can create a poverty trap. She argues that unequal distribution of human capital can affect aggregate product. In order to construct her argument, she creates a model in which education is financed privately. More vulnerable families will ask for higher human capital returns in order to finance education for their children. In this context, poverty traps can persist for generations.

Poverty traps can also appear because of geographical reasons, as explained in Kraay & McKenzie (2014). These geographical traps occur when a household in a certain area cannot increase its consumption while an identical household that only differs in its location would be able to enjoy a better standard of living. There are a number of reasons that could prevent people from moving out of the zones with a lower welfare. For example, uncertain property rights and the cost of moving. They find that the strongest evidence for a poverty trap at an individual level is based on the country of residence. This means that the same individual can remain stagnant or earn more depending on the country they work in. In this case, effective policies would include lowering migration barriers. Also, Jalan & Ravallion (2002) find evidence of geographical poverty traps in farm-household panel data from rural China for the years 1985-1990. They set to investigate why there are still areas with low living standards even in countries like China that have been growing economically. Underinvestment on publicly and privately provided goods and services can contribute to creating these traps.

On the other hand, there are a number of researchers that try to detect the existence of a poverty trap by observing the relationship in income dynamics at a household or individual level in a country. This approach includes estimating a nonlinear income model that relates income today to income from the previous period. One of the first studies in this area was that of Jalan & Ravallion (2004). They argue that if a poverty trap exists, poor households may never recover from a negative shock in their income, even if it is brief. This would imply that the most efficient policies and institutions would be those that protect households from temporary shocks. If incomes remain above the low-level unstable equilibrium, the poverty trap can be avoided. They then use panel data from households in south-west China to test for non-linearity in both income and expenditure dynamics in the period from 1985 to 1990. They examine non-linear dynamics using income (and expenditure) as a cubic function of its own lagged values, and instrumental variables. They are able to find some evidence of non-linearity but their results are not consistent with the existence of a poverty trap.

In a study that uses panel data from the 1990s, Lokshin & Ravallion (2004) study household income in Hungary and Russia. Due to households leaving the sample, they need to use a systems estimator to model attrition as a function of initial observed characteristics. They find nonlinear income dynamics but no evidence of an unstable equilibrium. That is, they do not find evidence of a trap in which a household will not be able to recover from a shock. However, they do find that the adjustment period is slower for more vulnerable households. Also using panel data, Santos (2010) tests for the presence of a poverty trap in income and expenditure in Perú. He uses data from 1998 to 2001 and allows for heterogeneity between households. He finds non-linear income dynamics and evidence of an unstable equilibrium in middle values of the sample, which he argues could confirm the existence of a poverty trap. The author also emphasizes the lack of works of this sort for Latin America compared to other regions.

However, Carter & Barrett (2005) explain that the use of short panels can lead to problems in distinguishing between structural poverty and transitory movements. There can also be problems with measurement errors. Therefore, some works on income mobility and poverty use pseudo panels instead of traditional panel data. Antman & McKenzie (2007b) demonstrate that dynamic pseudo panels can be used to consistently estimate the degree of income mobility. They argue that using panel data involves the presence of measurement error and nonrandom attrition. They apply a pseudo-panel approach to study household earning mobility in Mexico in the period 1987-2001 and find that absolute mobility levels are low. However, they detect rapid conditional mobility, which is the movement around a household's fixed effect.

Navarro (2010) uses dynamic pseudo-panels to estimate long term earnings mobility for male workers in Argentina with data from 1985 to 2004. The use of pseudo panels allows to relate the current earnings of a cohort with its past ones. In order to build the cohorts, employed men between 21 and 65 years of age are considered. Data from individual labor earnings in the *Encuesta Permanente de Hogares* (EPH) is used, specifically from Greater Buenos Aires (GBA). As it covers 20 years, it allows to estimate long term mobility and to analyze sub periods. The author finds some long term earnings mobility.

Antman & McKenzie (2007a) introduce the use of pseudo-panels to detect poverty traps in a study for Mexico. They first try using short traditional panels, in which they find no income dynamics that could indicate a trap, and also observe high income mobility. They claim this mobility could be the result of measurement errors. When using pseudo-panels, they allow for heterogeneity in modeling income dynamics, so that certain groups of individuals could be facing a poverty trap even if the average individual does not. They use data from 1987 to 2001 and divide the individuals in cohorts based on the household's head birth year and education level. They restrict the sample by only using cohorts which have at least 100 observations. Then they test for poverty traps in labor earnings, income, and expenditure. They find non-linearities in household income dynamics, but are unable to find evidence on the existence of a trap, even allowing for heterogeneity.

Casanova (2008) and Bertholet et al (2022) follow the methodology described in Antman & McKenzie (2007a) in an attempt to detect a poverty trap in urban areas of Argentina. They construct the cohorts in the same way as Navarro (2010), using data from the country's national household survey (*Encuesta Permanente de Hogares* - EPH). Both works find no evidence of a poverty trap. Casanova (2008) finds that the velocity at which households recover their income after a transitory shock is greater when their initial income is higher. Bertholet et al (2022) discriminate by gender and by the job insertion condition of the head of the household and note that, although a poverty trap does not seem to be present, a middle income trap could be considered.

In regards to Paraguay, Otter (2008) studies the connection between income mobility and growth from 1992 to 2002. He states that empirical evidence on the subject for Paraguay is inexistent and explains the importance of studying the determinants of growth at the household level, given the country's persistent high poverty rates at the time. To do so, he uses micro data and area welfare estimates, which are a combination of information from a census and a survey. These estimates were grouped in pseudo panels considering the age of the head of the household, number of schooling years, his mother tongue, his district and migration condition (so as not to include migrant households).

Also for Paraguay, in a study that falls in the first category of poverty trap literature (studying the mechanisms that lead to a poverty trap), Coronel Aguirre (2018) uses pseudo panels to empirically evaluate whether precarious employment affects the accumulation of assets and the level to which they converge in the long term. Thus, if precarious employment limits dynamic asset accumulation, it can lead to a poverty trap. Results show that the precarious groups converge to an equilibrium below the poverty line. Furthermore, Gonzalez, Ramirez & Perera (2011) use pseudo panels to analyze income dynamics and labor in Paraguay, using data from 1997 to 2008. They find relative stagnation in income and observe that the labor market is relevant in its distribution. They also notice that long term dynamics are different for men and women, as women have a flatter income curve. Both these studies use data from the *Encuesta Permanente de Hogares* (EPH) in Paraguay.

However, Paraguay remains an understudied field in regards to economic matters and our study contributes to existing literature by being the only work for Paraguay that attempts to detect a poverty trap using non linear income dynamics and pseudo panels, following Antman & McKenzie (2007a). Also, we divide the sample into rural and urban regions, in order to analyze each area separately, as they are exposed to different living conditions and poverty lines. Our elevated number of observations allows us to do so, compared to other works for Latin America which only focus on urban areas. Therefore, we can detect if there is a poverty trap in rural or urban areas, even if it is not present for the other group.

4 Pseudopanels

The presence of poverty traps is associated with non linear income dynamics. Estimations of income dynamics require panel data that follows households throughout a long period of time. The use of panels to detect poverty traps, however, is complicated by the lack of long panels that follow the same households, especially in developing countries (Antman & McKenzie, 2007a). Even if these were available, they can be subject to measurement errors and attrition problems. In cases of a lack of panel data where the same individuals are followed over a period of time, under certain conditions periodically repeated cross-section data can be used as a substitute. What can be done is to organize the data into cohorts, replace individual variables for their intra-cohort means and make estimates based on these values. The use of pseudo-panels is an extension of the within estimator.

Therefore, we will follow the methodology described in Antman and McKnenzie (2007a) to overcome the three issues that arise with regular panels: lack of long panels, possible attrition and measurement errors. They propose the use of pseudo-panels to estimate non lineal income dynamics. These estimations are then used to test for the presence of poverty traps.

Pseudo panels follow groups of households with similar characteristics, also referred to as cohorts. These cohorts are tracked over repeated cross-sectional surveys, which are usually periodically carried out in countries. As the cohorts are created every period with new samples, there is no risk of attrition. Furthermore, Antman and McKenzie (2007a) demonstrate that using pseudo panels solves estimation biases that were created by measurement errors for income. One limitation of pseudo panels is that things such as massive migration could alter the composition of the cohorts (Bertholet et al, 2022).[1]

Baltagi (2008) explains that, when using pseudo panels, one moves from equation (1) to (2):

$$y_{it} = x_{it}^{'}\beta + \mu_i + v_{it} \qquad t = 1, ..., T \tag{1}$$

$$\bar{y}_{ct} = \bar{x}_{ct}^{'}\beta + \bar{\mu}_{ct} + \bar{v}_{ct} \qquad c = 1, ..., C \qquad t = 1, ..., T \tag{2}$$

Here $\bar{y}_{ct}$ is the average y_{it} of all the individuals that belong to the cohort c at time t. Also, $\bar{\mu}_{ct}$ is a cohort fixed effect, where if $\bar{\mu}_{ct} \neq \bar{\mu}_c$ (it varies over time), it leads to an identification problem. Therefore, the identifying assumption is that $\bar{\mu}_{ct} = \bar{\mu}_c$. This assumption can hold as long as the number of observations in each cohort is large. This leads to (3):

[1] There was migration from Paraguay, but it was over the scope of many years, divided almost equally between women and men and mostly young people (Fondo de Población de las Naciones Unidas, 2013).

$$\bar{y}_{ct} = \bar{x}_{ct}^{'}\beta + \bar{\mu}_c + \bar{v}_{ct} \qquad c = 1, ..., C \qquad t = 1, ..., T \tag{3}$$

Deaton (1985) argues that the estimation with pseudopanels includes measurement errors, and suggests that one has to correct the within estimator obtained, estimating the errors in the measurement variance-covariance matrix from the survey data. Verbeek and Nijman (1993) maintain that with a large number of individuals per cohort, the measurement errors tend to zero. With at least 100 individuals per cohort, most applied researchers don't take into account the measurement errors and only estimate the within estimator. Verbeek and Nijman explain that, as well as having a large enough number of samples in each cohort, each one should be as homogeneous as possible. In addition, cohorts should be as heterogeneous as possible.

When constructing cohorts, what must be sought is to make the identification assumption, $\bar{\mu}_{ct} = \bar{\mu}_c$, as plausible as possible. In order to achieve this, cohorts must be constructed on a stable population and using a stable criterion (Guillerm, 2017). For example, Casanova (2008) restricts the sample of the population to people between 21 and 65 years old. Also, as explained before, cohorts should be large enough. Another aspect that must be kept is variability. When there is not a great amount of samples there is a tradeoff between cohort size and variability. Grouping close groups reduces the variability of the means over time.

Following Casanova (2008), we construct cohorts using the birth year of the head of the household and restrict the age from 21 years old to 65 years old. The pseudo panel relates present earnings of each cohort with past ones. Navarro (2010) argues that cohorts are less appropriate to estimate mobility at early or late stages of life. This is because younger cohorts can change its distribution if new households are being formed, and household dissolution can happen in older cohorts if people are dying. As long as the population is not significantly affected by immigration and emigration and the members of cohorts are not dying in large numbers, successive surveys can be used to follow each cohort (Deaton, 1997). This "allows us to disentangle the generational from life-cycle components in income and consumption profiles" (Deaton, 1997, p.117).

Casanova (2008) and Navarro (2010) use 5 year bands, so that low number of observations are avoided and the middle point can be used as the defining age. We use the same age range in this study, which is consistent with other works in Latin America, and therefore makes results comparable with existing literature. We divide by rural and urban areas to explore whether their situations are different. Only 3 out of the 163 year-cohort combinations for rural areas have less than 100 observations, and all combinations for urban areas have more than 100. Sometimes, cohorts can be defined by age and other observable characteristics, such as education, but this would restrict the number of observations in each cohort. Also, education is a variable that can change over time, so it is not ideal to build cohorts this way.

	Cohort										
Year	1	2	3	4	5	6	7	8	9	10	11
2002				22-26	27-31	32-36	37-41	42-46	47-51	52-56	57-61
2003				23-27	28-32	33-37	38-42	43-47	48-52	53-57	58-62
2004				24-28	29-33	34-38	39-43	44-48	49-53	54-58	59-63
2005				25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
2006			21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	61-65
2007			22-26	27-31	32-36	37-41	42-46	47-51	52-56	57-61	
2008			23-27	28-32	33-37	38-42	43-47	48-52	53-57	58-62	
2009			24-28	29-33	34-38	39-43	44-48	49-53	54-58	59-63	
2010			25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	
2011		21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	61-65	
2012		22-26	27-31	32-36	37-41	42-46	47-51	52-56	57-61		
2013		23-27	28-32	33-37	38-42	43-47	48-52	53-57	58-62		
2014		24-28	29-33	34-38	39-43	44-48	49-53	54-58	59-63		
2015		25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64		
2016	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	61-65		
2017	22-26	27-31	32-36	37-41	42-46	47-51	52-56	57-61			
2018	23-27	28-32	33-37	38-42	43-47	48-52	53-57	58-62			
2019	24-28	29-33	34-38	39-43	44-48	49-53	54-58	59-63			
2020	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64			
2021	26-30	31-35	36-40	41-45	46-50	51-55	56-60	61-65			

Figure 1: Age ranges of the head of the household in each year-cohort combination

5 Data

We use data from 2002 to 2021, taken from the *Encuesta Permanente de Hogares (EPH)* (household survey) collected by the *Instituto Nacional de Estadística (INE)* in Paraguay. Household surveys are available annually from 1999, but only without interruptions since 2002 and in a comparable series. Starting in 2022, the survey changed to *Encuesta Permanente de Hogares Continua (EPHC)*, in which data is taken every trimester. As explained in Navarro (2010), only including annual measurements can be beneficial since it is difficult to define the age of individuals in different moments of the year. We could have used data from the latest issues for a particular trimester, but, since the survey is not the same, we opted to keep the data consistent.

The years we use are available as a comparable series, meaning surveys were executed at the same time each year (fourth trimester), with the same geographical distribution and same methodology. We cover 20 years, which is more than sufficient to detect long-term changes (Navarro, 2010). We divide the sample into rural and urban areas (as classified in the household surveys). There is enough data in each area for the correct assembly of cohorts.

The variable for income is monthly family income per capita, which takes family income and divides it by the total members of the household. Family income adds every sort of income reported, from main and secondary activities, as well as other sources. Values are deflated by the INE to express income in prices of the central month of the trimester of each particular year. This means that variables are expressed in current or nominal prices for that particular year. For example, income for 2008 is based on November 2008 prices. We further deflated the values

so that different years could be comparable, using the official CPI. For the official price index, Paraguay's government does not distinguish between rural and urban areas.

Income is self-reported in the survey, thus there is room for missing values or people that report an income of zero. However, all information is guaranteed to be confidential and protected, which should reduce incentives to do this. When income is not reported, the procedure followed by the *INE* is different depending on the individual. For salary men, a proxy mean test is used (multiple regression models). For independent workers (agricultural or non-agricultural), net income is calculated based on specific modules that allow to balance their production. The number of unreported income is low. This is also the case for income of zero, which we removed from the sample following Navarro (2010). Outliers were handled by replacing everything above the 99th percentile with the 99th percentile for each year, so as to not loose observations.

	1	2	3	4	5	6	7	8	9	10	11
2002				523,892.16	387,626.58	507,153.84	475,756.49	357,669.70	471,363.32	523,368.77	494,249.61
2003				527,029.80	523,329.99	547,699.12	512,205.72	523,331.23	596,019.66	553,146.48	561,437.44
2004				592,031.91	649,823.81	534,894.28	586,119.50	580,693.41	619,307.67	541,988.90	638,630.21
2005				601,980.16	570,284.86	519,875.74	531,601.24	545,869.53	643,110.29	650,995.82	776,082.67
2006			568,530.98	616,856.24	474,779.66	500,294.26	518,583.15	572,537.64	621,684.42	600,848.12	613,688.09
2007			636,454.48	630,441.47	548,170.64	604,049.77	536,670.91	527,689.18	605,674.87	688,958.88	
2008			687,125.95	529,606.71	613,999.70	561,390.11	645,237.48	721,445.93	683,665.19	703,065.16	
2009			606,946.29	610,355.30	495,992.51	585,160.95	566,640.31	721,167.07	696,300.07	604,564.85	
2010			784,103.10	736,183.40	650,615.40	595,206.90	683,204.50	597,933.20	677,922.10	600,413.60	
2011		868,852.77	708,444.88	874,473.99	657,739.31	662,759.72	809,618.45	681,048.57	894,690.07	643,115.36	
2012		809,565.81	632,335.61	675,409.64	695,658.89	592,331.62	703,675.76	719,837.81	970,985.47		
2013		759,633.88	822,275.91	747,796.89	696,180.20	822,029.48	663,185.50	853,373.01	772,598.30		
2014		882,367.32	1,030,525.41	977,838.29	856,110.92	794,328.78	804,530.87	930,463.43	832,664.31		
2015		684,145.87	796,669.75	724,307.02	676,164.11	744,800.28	751,439.08	685,932.00	755,931.97		
2016	862,204.40	781,666.33	761,180.05	669,239.83	695,565.11	779,545.19	742,514.13	776,124.11	786,674.42		
2017	982,737.18	791,291.58	779,652.07	1,152,739.45	886,759.57	860,285.42	772,241.81	905,995.06			
2018	805,109.10	815,957.04	851,753.14	807,301.13	830,743.18	792,932.24	770,389.00	732,447.32			
2019	906,173.39	985,909.98	815,260.40	851,020.12	858,833.31	794,189.08	891,706.10	732,155.04			
2020	824,595.81	781,852.80	722,054.94	737,202.20	771,879.66	768,739.52	752,596.79	787,437.54			
2021	794,479.70	673,677.16	682,382.20	756,491.41	764,413.38	823,607.12	843,756.97	770,485.59			

Figure 2: Average income (deflated) for each cohort-year combination for rural areas

	1	2	3	4	5	6	7	8	9	10	11
2002				936,708.04	842,554.88	929,484.30	973,234.66	811,097.67	1,003,678.33	1,092,288.90	1,288,132.95
2003				905,485.55	845,008.58	869,531.60	876,708.37	942,895.82	1,067,148.56	1,086,355.32	1,084,689.38
2004				919,323.13	949,882.90	921,838.22	861,146.45	930,856.76	990,992.42	949,848.01	1,177,465.15
2005				1,090,766.24	963,835.85	1,070,619.94	1,115,741.45	1,094,923.80	1,044,468.01	1,238,153.63	1,238,319.48
2006			1,188,739.36	1,033,863.40	941,015.93	911,325.30	1,018,094.76	996,540.26	983,062.57	1,180,609.29	1,139,892.55
2007			1,141,239.45	1,026,607.69	961,789.89	940,940.36	1,026,178.63	1,162,057.60	1,170,263.58	1,239,617.79	
2008			1,038,377.68	1,060,835.76	1,025,568.28	950,405.49	947,333.69	1,154,580.03	1,133,577.11	1,187,003.29	
2009			1,262,105.93	1,180,141.32	1,035,755.99	1,009,695.44	1,117,551.34	1,194,365.93	1,088,954.88	1,431,674.75	
2010			1,214,287.96	1,099,951.71	1,095,388.34	1,204,624.91	1,263,306.16	1,208,344.60	1,301,838.05	1,587,894.42	
2011		1,276,602.55	1,225,503.69	1,340,846.90	975,551.83	1,134,085.03	1,143,900.62	1,356,793.80	1,337,998.23	1,196,052.86	
2012		1,392,995.74	1,322,141.96	1,301,796.05	1,171,118.70	1,167,068.30	1,258,157.60	1,313,182.73	1,468,492.75		
2013		1,358,674.95	1,542,818.78	1,476,870.10	1,240,551.80	1,354,577.26	1,510,243.63	1,590,346.32	1,482,138.70		
2014		1,195,454.15	1,347,292.80	1,265,478.49	1,210,274.06	1,297,767.36	1,330,086.74	1,558,714.34	1,546,704.68		
2015		1,277,428.69	1,317,459.21	1,277,220.51	1,225,605.44	1,414,055.97	1,446,522.53	1,429,356.70	1,428,057.72		
2016	1,192,375.31	1,281,565.52	1,317,566.79	1,275,971.82	1,220,331.25	1,318,368.74	1,485,245.06	1,423,777.71	1,553,057.60		
2017	1,291,050.72	1,410,673.77	1,196,834.65	1,280,200.16	1,371,239.94	1,373,749.00	1,496,651.25	1,669,215.43			
2018	1,513,110.75	1,507,253.07	1,496,024.33	1,282,814.44	1,438,601.18	1,509,976.08	1,547,466.54	1,819,216.16			
2019	1,422,315.07	1,602,820.90	1,415,498.16	1,326,491.52	1,449,283.31	1,616,554.01	1,758,913.47	1,814,954.82			
2020	1,222,233.47	1,292,209.25	1,218,836.09	1,272,535.39	1,351,776.34	1,412,505.48	1,412,240.14	1,503,274.06			
2021	1,266,706.30	1,385,944.11	1,278,946.57	1,263,972.74	1,357,642.56	1,355,556.45	1,450,774.10	1,540,757.59			

Figure 3: Average income (deflated) for each cohort-year combination for urban areas

6 Method

6.1 Panel data without measurement error

Let us first look at a hypothetical case where we have a traditional panel with no measurement error. To test for non-linearity in income and the existence of multiple equilibria, one can follow the methodology described by Antman & McKenzie (2007a) and Casanova (2008) in modeling non linear income dynamics as a cubic form of the lagged dependent variable and including unobserved individual effects α_i. This last parameter allows for individual heterogeneity (differences among individuals) so that some groups may be subject to a poverty trap even if others are not. Also, temporary income shocks can be written as $\mu_{i,t}$. Thus, household income in period t is written as a polynomial function of third degree of lagged income with the following equation:

$$Y_{i,t} = \beta_1 Y_{i,t-1} + \beta_2 (Y_{i,t-1})^2 + \beta_3 (Y_{i,t-1})^3 + \alpha_i + \mu_{i,t} \tag{4}$$

With the parameters $\beta_1, \beta_2, \beta_3$ significantly different from zero we can see if there are non convexities in the income dynamics (as in figure 4), which could indicate the presence of a poverty trap. The point of equilibrium could be different between households because of α_i (the intercept in figure 4), but the adjustment process is the same for everyone.

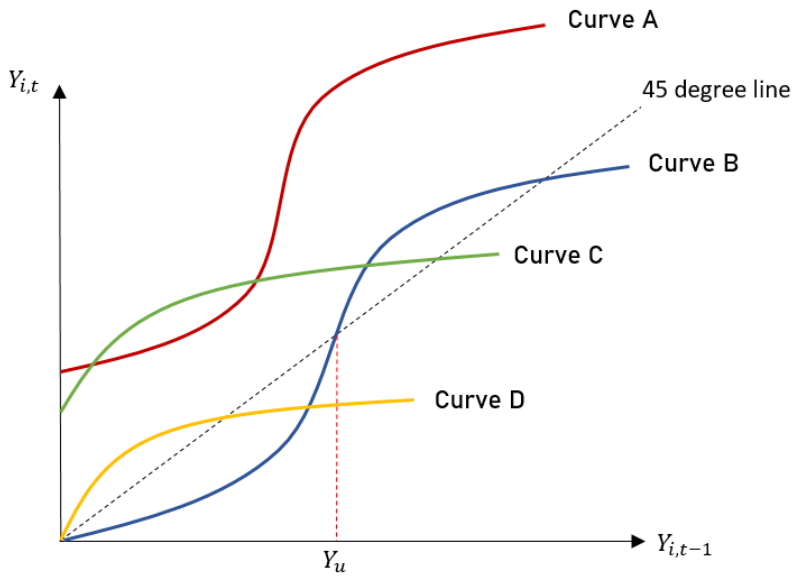


Figure 4: Possible cases of income dynamics. Own figure, inspired by Casanova (2008).

Y represents household income for periods t and $t-1$. Y_u is the poverty line or the minimum level of substance. The 45 degree line represents dynamic equilibria in which income today is the same as its lagged value. These equilibriums can either be stable or unstable. Above the line, income grows with t (because income tomorrow is greater than income today), while the contrary occurs below.

Curve A displays nonlinear income dynamics but no poverty trap as it rests entirely above the 45 degree line, meaning income is always greater in t than in $t-1$. Curve C, on the other hand, has one equilibrium above the threshold, so again no poverty trap is present.

The figure illustrates two cases of poverty traps: curves D and B. For curve D, there is a stable equilibrium that is below the level of subsistence income. If a shock occurs that leaves income to the left of the line, it will rise (as income in t is greater than income in $t-1$ at that stretch), but it will reach a steady state below the poverty line. If a shock leaves income to the right, it will fall until it reaches the same steady state. This means the household is stuck in a poverty trap, no matter the shock.

For curve B, we have a case of multiple equilibria. The income curve first cuts the 45 degree line from below, thus poverty trap arises if the household gets trapped in an income below the threshold Y_u (because income is decreasing). We can see if we are in this case by checking if:

$$g_i^{'}(Y_{i,t-1})|_{Y_{i,t}=Y_{i,t-1}} > 1 \tag{5}$$

where g determines income in t as a function of income in $t-1$, so that $Y_{i,t}^{*} = g\left(Y_{i,t-1}^{*}\right)$. Then, g' is the derivative of this income function. So, this conditions specifies that the derivative in the 45 degree line must be greater than 1. This detects cuts of the income function from below the 45 degree line. The stability of the equilibria is dependent on the slope of the tangent line that cuts the curve at that point. When it is greater than 1, the equilibrium is unstable, and it is stable when it is less than 1. Curve B also cuts the 45 degree line far away from the poverty line, but in that case the derivative is less than 1, so it will not be taken into account by equation (5). If a household finds itself in the path before this second cut and a shock occurs, income will rise (as they are above the 45 degree line), and the household will revert to the stable equilibrium above the poverty line.

The OLS method can be used to estimate coefficients β_1, β_2 and β_3 in equation (4), using monthly family income per capita (for each cohort). Therefore, each point in a graph represents income for one cohort in t and $t-1$ for each combination of successive years. If β_2 and β_3 are significant, the roots of the equation must be calculated, where income in t is the same as income in $t-1$. In figure 4, these are the point where the income function crosses the 45 degree line. Then, the derivative of the function in the point Y_u must be calculated, in order to check whether it is greater to 1 and whether the intersection calculated before is above the poverty line or not.

If a poverty trap is not detected, it is possible to calculate the speed at which households will recover from an adverse shock, by using the concavity of the function.

To calculate the fixed effect, we have to estimate the following equation:

$$\hat{\alpha}_i = \bar{Y}_{i,t} - \hat{\beta}_1 \cdot \bar{Y}_{i,t-1} - \hat{\beta}_2 \cdot \bar{Y}^2_{i,t-1} - \hat{\beta}_3 \cdot \bar{Y}^3_{i,t-1} \tag{6}$$

where $\bar{Y}_i = \left(\frac{1}{T-1}\right) \cdot \sum_{t=2}^{T} Y^*_{i,t}$ and $\bar{Y}^s_{i,t-1} = \left(\frac{1}{T-1}\right) \cdot \sum_{t=2}^{T} \left(Y^*_{i,t-1}\right)^s$, $s = 1, 2, 3$.

Equation (5) is satisfied if:

$$\hat{\beta}_1 + 2 \cdot \hat{\beta}_2 \cdot \left(Y^*_{i,t-1}\right) + 3 \cdot \hat{\beta}_3 \left(Y^*_{i,t-1}\right)^2 > 1 \tag{7}$$

This condition must be evaluated in $Y^*_{i,t} = Y^*_{i,t-1}$ and when $\mu_{i,t} = 0$ (the expected shock), that is, in:

$$Y^*_{i,t} = \hat{\beta}_1 \cdot Y^*_{i,t} + \hat{\beta}_2 \cdot \left(Y^*_{i,t}\right)^2 + \hat{\beta}_3 \cdot \left(Y^*_{i,t}\right)^3 + \hat{\alpha}_i \tag{8}$$

6.2 Panel data with measurement error

However, Antman & McKenzie (2007a) note that, in practice, one does not observe real income $Y^*_{i,t}$ but rather $Y_{i,t} = Y^*_{i,t} + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ is the measurement error. The error is assumed to have a mean of zero and be independently distributed across individuals with $E\left(\varepsilon^2_{i,t}\right) = \sigma^2_\varepsilon$.

We then have:

$$Y_{i,t} = \beta_1 Y_{i,t-1} + \beta_2 \left(Y_{i,t-1}\right)^2 + \beta_3 \left(Y_{i,t-1}\right)^3 + \alpha_i + \eta_{i,t} \tag{9}$$

where [2]

$$\eta_{i,t} = \mu_{i,t} + \varepsilon_{i,t} - \left(\beta_1 + 2\beta_2 Y_{i,t-1} + 3\beta_3 Y^2_{i,t-1}\right) \varepsilon_{i,t-1} + \left(\beta_2 + 3\beta_3 Y_{i,t-1}\right) \varepsilon^2_{i,t-1} - \beta_3 \varepsilon^3_{i,t-1} \tag{10}$$

The OLS estimation of the model turns out inconsistent estimators. It can even bias the estimation of β_1 towards zero. This would lead to the incorrect conclusion that there is less persistence in the income process. Furthermore, for most cases the Arellano-Bond instrumental variable approach will also be inconsistent. Even if there are no measurement errors, attrition can lead to inconsistent estimators (Casanova, 2008).

6.3 Using pseudo panels

We follow the strategy presented by Antman & McKenzie (2007a) of using pseudo panels to estimate income dynamics consistently. They demonstrate that pseudo panels can deal with measurement error problems present in panel data models.

We can take cohort averages of equation (9) over n_c households observed in cohort c at time

[2] Demonstration for η in appendix

t in order to get to:

$$\bar{Y}_{c(t),t} = \beta_1 \bar{Y}_{c(t),t-1} + \beta_2 \left[\frac{1}{n_c} \sum_{i=1}^{n_c} Y^2_{i(t),t-1} \right] + \beta_3 \left[\frac{1}{n_c} \sum_{i=1}^{n_c} Y^3_{i(t),t-1} \right] + \alpha_c + \bar{\eta}_{c(t),t} \tag{11}$$

where $\bar{Y}_{c(t),t} = (1/n_c) \sum_{i=1}^{n_c} Y_{i(t),t}$ is the simple mean of income over the individuals in cohort c at time t. As with pseudo panels different individuals are used each period, $\bar{Y}_{c(t),t-1}$ is not observed. The same thing happens with the mean of the lagged square income and the mean of the lagged cubic income. These terms are then replaced with the means of the individuals who are observed at $t-1$.

The equation becomes:

$$\bar{Y}_{c(t),t} = \alpha_{c(t)} + \beta_1 \cdot \bar{Y}_{c(t-1),t-1} + \beta_2 \left[\frac{1}{n_c} \cdot \sum_{i=1}^{n_c} Y^2_{i(t-1),t-1} \right] + \beta_3 \left[\frac{1}{n_c} \cdot \sum_{i=1}^{n_c} Y^3_{i(t-1),t-1} \right] + \bar{\eta}_{c(t),t} + \bar{\lambda}_{c(t),t} \tag{12}$$

with:

$$\lambda_{c(t),t} = \beta_1 \left(\bar{Y}_{c(t),t-1} - \bar{Y}_{c(t-1),t-1} \right) + \beta_2 \frac{1}{n_c} \left(\sum_{i=1}^{n_c} Y^2_{i(t),t-1} - \sum_{i=1}^{n_c} Y^2_{i(t-1),t-1} \right)$$

$$+ \beta_3 \frac{1}{n_c} \left(\sum_{i=1}^{n_c} Y^3_{i(t),t-1} - \sum_{i=1}^{n_c} Y^3_{i(t-1),t-1} \right) \tag{13}$$

$\lambda_{c(t),t}$ includes measurement errors that appear because of observing different households in each period. Notice that between each parenthesis we have the difference between using the same individuals and what we actually observe. However, McKenzie (2004) proves that, as the number of individuals in each cohort tends to larger numbers, $\lambda_{c(t),t}$ tends to zero for the linear case. This requires that $\bar{Y}_{c(t),t-1}$ and $\bar{Y}_{c(t-1),t-1}$ converge to the same mean as the sample size tends to infinity. For a cubic model as ours, it is also requires that $\left(\frac{1}{n_c}\right) \cdot \left(\sum_{i=1}^{n_c} Y^2_{i(t),t-1}\right)$ and $\left(\frac{1}{n_c}\right) \cdot \left(\sum_{i=1}^{n_c} Y_{i(t-1),t-1}\right)$ tend to the same mean, as well as $\left(\frac{1}{n_c}\right) \cdot \left(\sum_{i=1}^{n_c} Y^3_{i(t),t-1}\right)$ and $\left(\frac{1}{n_c}\right) \cdot \left(\sum_{i=1}^{n_c} Y^3_{i(t-1),t-1}\right)$. This might not hold if changes are introduced in the survey. However, given that we use a comparable series that applies the same methodology each year, we can assume $\lambda_{c(t),t}$ tends to zero.

We got rid of $\lambda_{c(t),t}$ but need to work on $\bar{\eta}_{c(t),t}$. From (10) we can get the following if we use cohort means:

$$\bar{\eta}_{c(t),t} = \bar{\mu}_{c(t),t} + \bar{\varepsilon}_{c(t),t} - \left(\frac{1}{n_c} \right) \cdot \sum_{i=1}^{n_c} \left[(\beta_1 + 2\beta_2 Y_{i,t-1} + 3\beta_3 Y^2_{i,t-1}) \varepsilon_{i(t),t-1} \right]$$

$$+\left(\frac{1}{n_c}\right)\sum_{i=1}^{n_c}\left[(\beta_2+3\beta_3 Y_{i,t-1})\varepsilon^2_{i(t),t-1}\right]-\beta_3\left(\frac{1}{n_c}\right)\sum_{i=1}^{n_c}\varepsilon^3_{i(t),t-1} \tag{14}$$

Under certain assumptions, we can correct the bias present with non-classical measurement errors. Let us first consider a linear case, where β_2 and β_3 are zero, so that equation (12) becomes (taking into account (14)):

$$\bar{Y}_{c(t),t}=\beta_1\cdot\bar{Y}_{c(t-1),t-1}+\alpha_{c(t),t}+\bar{\varepsilon}_{c(t),t}-\beta_1\cdot\bar{\varepsilon}_{c(t),t-1} \tag{15}$$

As Antman & McKenzie (2007a) have demonstrated, when there is no cohort specific component in the measurement error, as the number of households in each cohort tends to infinity the following will happen:

$$\bar{\varepsilon}_{c(t),t}=\left(\frac{1}{\eta_c}\right)\sum_{l=1}^{\eta_c}\varepsilon_{i(t),t}\xrightarrow{p}E(\varepsilon_{i(t),t})=0 \tag{16}$$

Therefore, as long as the number of households per cohort remains large, β_1 and α_c (the cohort specific fixed effect) can be estimated through OLS and will be consistent.

When we are not in the presence of a linear case, as in our a non-linear dynamic, OLS estimations of β_1, β_2 and β_3 will still be consistent in the equation of cohort averages. On the other hand, α_c will not. In order to correct this estimation bias, it becomes necessary to set a series of new assumptions. These are the following:

1. Measurement errors are symmetric: $E(\varepsilon^3_{i,t})=0$.

2. Measurement errors are stationary, that is, $E(\varepsilon^2_{i,t})=\sigma^2_\varepsilon$ remains constant in time.

3. Measurement errors are independent from the actual values in each cohort. This means that $\varepsilon_{i,t}$ is independent from $Y^*_{i,t}$ for every i inside a cohort.

Given that data is generated by different households in each period, serial correlation between measurement errors is not a problem. Therefore, no assumptions on this matter are needed.

Taken all of this into account, it has been demonstrated that when n_c tends to infinity:

$$\bar{\eta}_{c(t),t}\xrightarrow{p}-\beta_2\cdot\sigma^2_\varepsilon-3\cdot\beta_3\cdot E_c(Y^*_{i,t-1})\cdot\sigma^2_\varepsilon \tag{17}$$

The OLS estimation of α_c tends to:

$$\hat{\alpha}_c \xrightarrow{p} \alpha_c - \beta_2 \cdot \sigma_\varepsilon^2 - 3 \cdot \beta_3 \cdot E_c(Y^*_{i,t-1}) \cdot \sigma_\varepsilon^2 \tag{18}$$

So that the actual α_c is the estimated $\hat{\alpha}_c$ plus another term:

$$\alpha_c \approx \hat{\alpha}_c + \beta_2 \cdot \sigma_\varepsilon^2 - 3 \cdot \beta_3 \cdot E_c(Y^*_{i,t-1}) \cdot \sigma_\varepsilon^2$$

The first two assumptions let us calculate the following variance:

$$Var(Y_{i,t}) = Var(Y^*_{i,t}) + \sigma_\varepsilon^2 \tag{19}$$

Which we can rearrange to:

$$\hat{\sigma}_\varepsilon^2 = Var(Y_{i,t}) \cdot \left(1 - \frac{Var(Y^*_{i,t})}{Var(Y_{i,t})}\right) \tag{20}$$

Equation (20) is used to estimate σ_ε^2. For this, the cross section variance of income is needed ($Var(Y_{i,t})$) as well $\theta = (Var(Y^*_{i,t})/Var(Y_{i,t}))$. Antman & McKenzie (2007a) follow a method described in Bound et al (2001) of using different values for θ to cover a large range of possible values. They use 0.5 and 0.8. We use 0.5, 0.65, 0.8 and 0.95 as in Casanova (2008).

Considering the expected value of the measurement error as zero, it is possible to estimate $E_c(Y^*_{i,t-1})$ with the average of $\bar{Y}_{c(t-1),t-1}$. This way, α_c can be estimated:

$$\tilde{\alpha_c} = \hat{\alpha_c} + \hat{\beta}_2 \cdot \hat{\sigma}_\varepsilon^2 + 3 \cdot \hat{\beta}_3 \cdot \bar{Y}_{c(t-1),t-1} \cdot \hat{\sigma}_\varepsilon^2 \tag{20}$$

With assumptions 1 and 2, when the number of households per cohort tends to infinity, $\tilde{\alpha}_c$ becomes a good estimator for the cohort effect α_c.

We can then go back to equations (7) and (8) at the cohort mean level:

$$\hat{\beta}_1 + 2 \cdot \hat{\beta}_2 \cdot \left(Y^*_{i,t-1}\right) + 3 \cdot \hat{\beta}_3 \left(Y^*_{i,t-1}\right)^2 > 1$$

$$Y^*_{i,t} = \hat{\beta}_1 \cdot Y^*_{i,t} + \hat{\beta}_2 \cdot \left(Y^*_{i,t}\right)^2 + \hat{\beta}_3 \cdot \left(Y^*_{i,t}\right)^3 + \hat{\alpha}_i$$

We can estimate whether a specific cohort is under a poverty trap if the first equation is fulfilled (the slope of the estimated income function at the 45-degree line is more than one). Heterogenities are allowed at a household level, but the intercept of the function is estimated

only for each cohort, so that the test for poverty trap is only for the average individual within each cohort.

7 Results

We estimate equation (12) considering the linear, quadratic and cubic cases for both urban and rural areas. If β_2 (the coefficient for the quadratic term) and β_3 (the coefficient for the cubic term) are statistically significant, we can say there is evidence of non-linearities in income dynamics. In this case, we correct the biased constant in the quadratic and cubic estimations with different values of $\theta - 0.5, 0.65, 0.80, 0.95$.[3] This is not necessary for the lineal case.

We verify the derivatives and roots of the income function. Let us recall than in order to have a poverty trap either (1) a stable equilibrium should be smaller than the poverty line as in curve A in Figure 4, or (2) the derivative should be greater than 1 as in curve B of Figure 4, giving an unstable equilibrium. The poverty line in 2010 was 493061 guaraníes for urban areas (187637 for extreme poverty) and 352073 guaraníes for rural areas (171357 for extreme poverty).[4]

7.1 Rural areas

7.1.1 No controls (unconditional convergence)

In this case, $\alpha_c = 0$, so we do not control by fixed effects at the cohort level.

Table 1: Estimation for rural areas without cohort fixed effects

	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$
$\hat{\beta}_1$	0.585***	0.679***	0.8274***
	(0.0572)	(0.0673)	(1.063e-01)
$\hat{\beta}_2$		-1.35e-08**	-6.13e-08**
		(5.38e-09)	(2.71e-08)
$\hat{\beta}_3$			8.580e-16*
			(4.769e-16)
Observations	152	152	152
R-squared	0.3264	0.3504	0.3626
Number of Cohort	11	11	11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[3] Graphs are included only for $\theta = 0.5$ and $\theta = 0.95$

[4] Poverty lines are not displayed in the figures as they are out of range.

Although the values are small, β_2 (in the quadratic and cubic specification) and β_3 (in the cubic specification) are statistically significant, which means there is evidence of non linearities in income dynamics. A graphic representation is shown in Figure 5. For all cases, income in t is increasing on income in $t-1$ and it cuts the 45 degree line from above. This would indicate that there is no poverty trap. The crossings are all at high income values.

As it was said before, the constant for the quadratic and cubic models is biased and needs to be corrected. Results with constant correction are portrayed in Figure 6 for $\theta = 0.5$ and in Figure 7 for $\theta = 0.95$. Previous findings are maintained.

Figure 5: Estimations without fixed effects and no bias correction

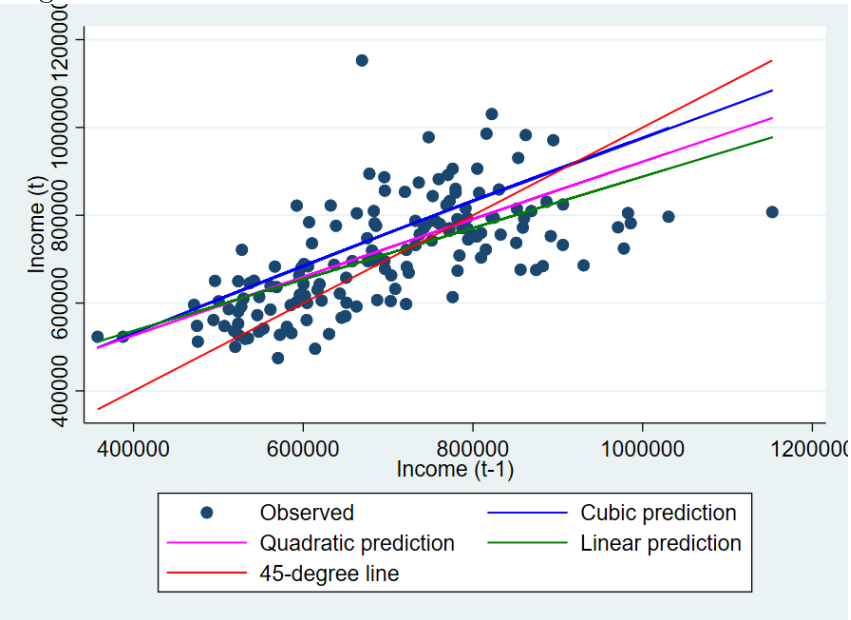


Figure 6: Estimations without fixed effects and constant correction ($\theta = 0.5$)

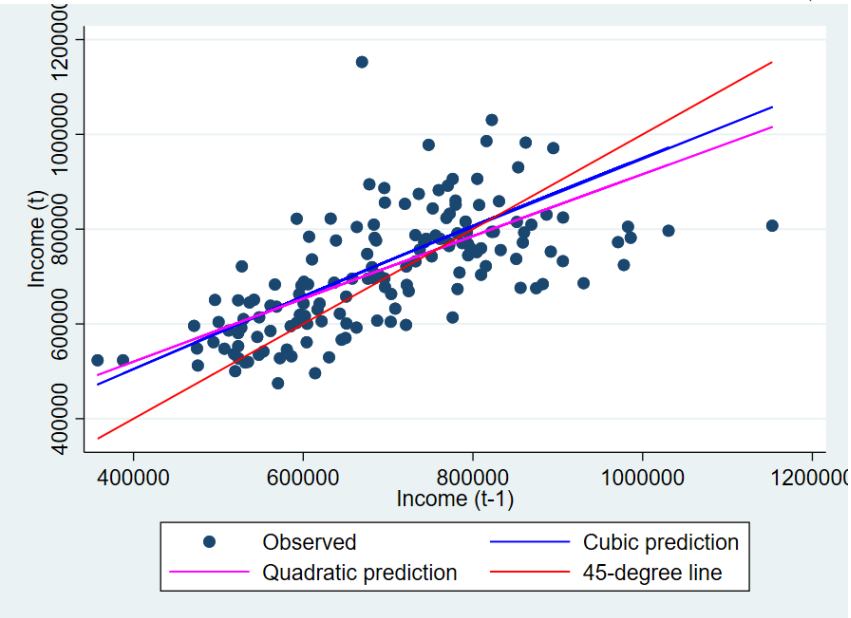
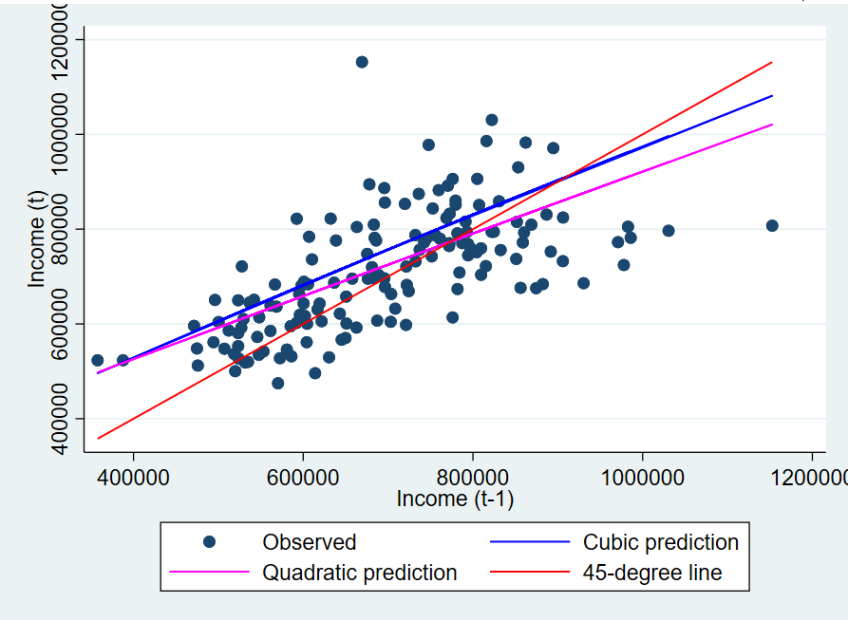


Figure 7: Estimations without fixed effects and constant correction ($\theta = 0.95$)



7.1.2 With controls (conditional convergence)

Conditional convergence controls for heterogenity between cohorts and fixed effects. Estimation without fixed effects could be inconsistent if there are fixed effects in the error term that are correlated with the independent variables. In order to fix this, dummies for the cohorts are added. Results are in Table 2 and they are similar to the case without fixed effects, but for $\hat{\beta}_3$ which is not statistically significant.

Table 2: Estimation for rural areas with cohort fixed effects

	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$
$\hat{\beta}_1$	0.530***	0.629***	0.7904***
	(0.0644)	(0.0770)	(1.253e-01)
$\hat{\beta}_2$		-1.29e-08**	-6.09e-08**
		(5.70e-09)	(3.01e-08)
$\hat{\beta}_3$			8.555e-16
			(5.264e-16)
Observations	152	152	152
R-squared	0.326	0.350	0.3626
Number of Cohort	11	11	11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 8 shows that the income function is close to the case without fixed effects. This is also the case after constant correction, as portrayed in Figures 9 and 10. The cubic model is

omitted for its lack of significance.

Figure 8: Estimations with cohort fixed effects and no bias correction

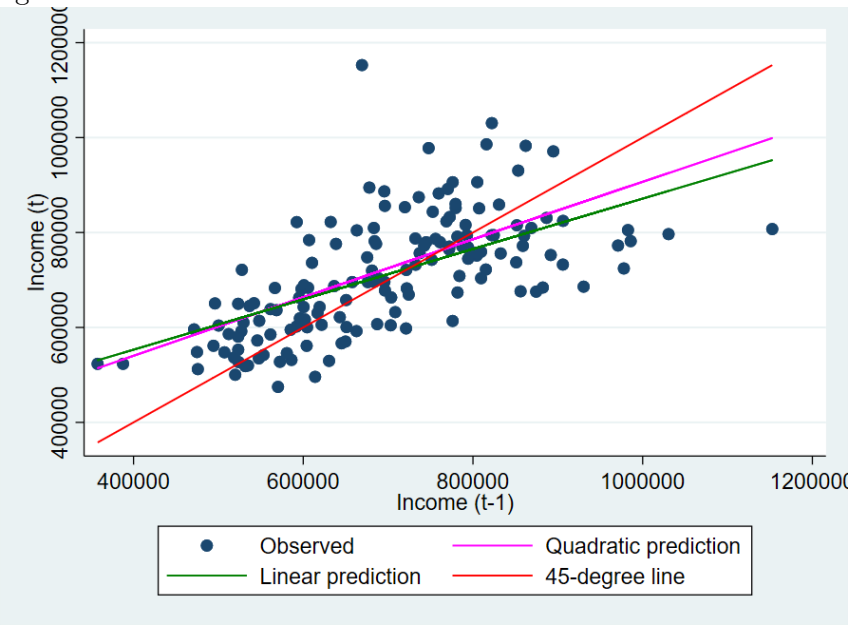


Figure 9: Estimations with cohort fixed effects and constant correction ($\theta = 0.5$)

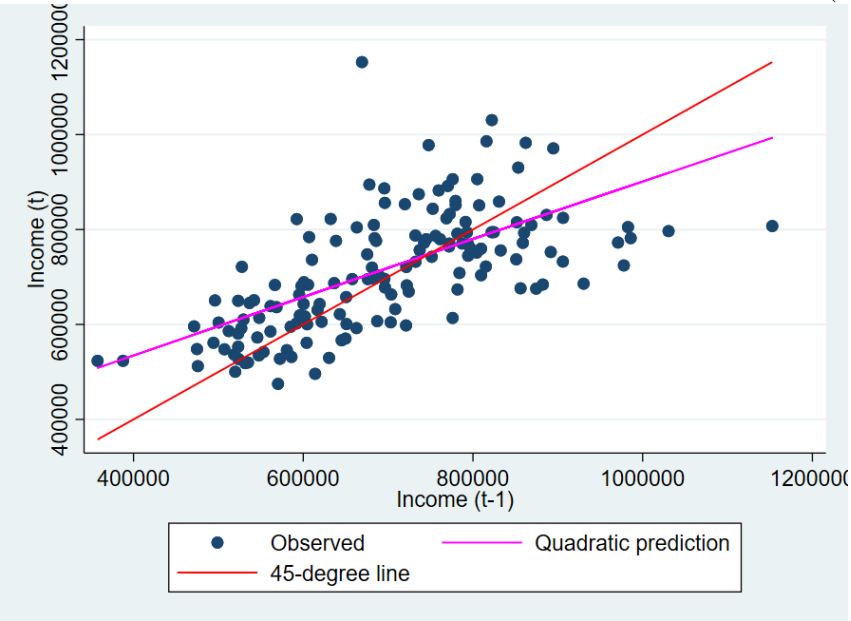
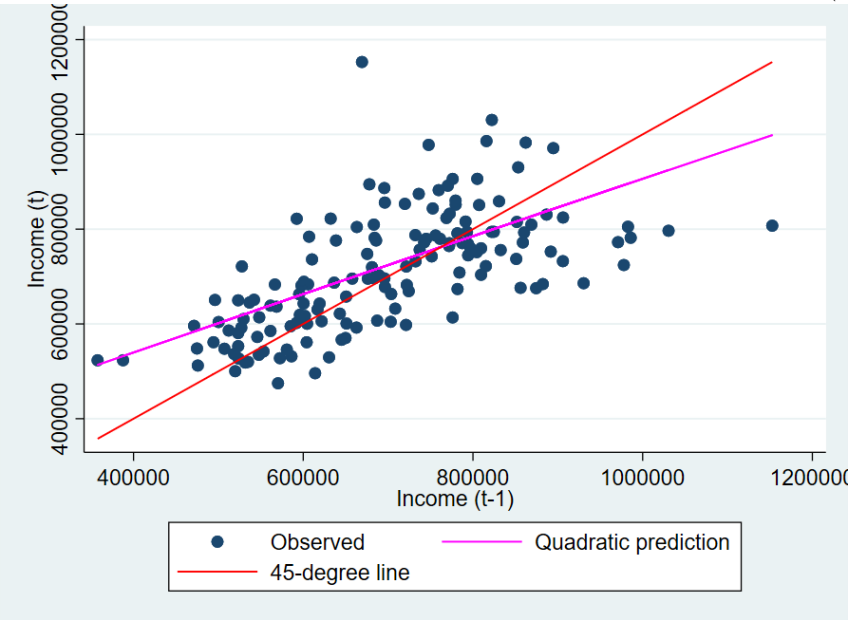


Figure 10: Estimations with cohort fixed effects and constant correction ($\theta = 0.95$)



Then, we include year fixed effects by adding dummies for the years. Results for this case are in Table 3. None of the coefficients are statistically significant. If the country has experimented large macroeconomic changes that affected the distribution of income, year fixed effects could absorb these reactions and decrease the probability of finding a poverty trap.

Table 3: Estimation with cohort and year fixed effects

	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$
$\hat{\beta}_1$	0.0451	0.07896	0.06023
	(0.0920)	(1.119e-01)	(1.983e-01)
$\hat{\beta}_2$		-2.69e-09	1.47e-09
		(5.04e-09)	(3.66e-08)
$\hat{\beta}_3$			-6.805e-17
			(5.936e-16)
Observations	152	152	152
R-squared	0.718	0.7186	0.7186
Number of Cohort	11	11	11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.1.3 Roots and derivatives

As it was observed in the graphs, Tables 4 and 5 show that, for every case, the roots are above the poverty line and derivatives are all less than one.[5] Thus, we can reject the existence of a poverty trap in rural areas by our method.

	Linear		**Quadratic**		**Cubic**	
	Solution	Derivative	Solution	Derivative	Solution	Derivative
No correction	730162.85	0.58546	775274.56	0.6577	922085.32	0.7166
Theta = 0.5			757656.00	0.6582	826468.81	0.7279
Theta = 0.65			762944.13	0.6580	855565.28	0.7244
Theta = 0.80			768239.09	0.6579	884303.12	0.7210
Theta = 0.95			773513.80	0.6578	912695.67	0.7177

Table 4: Roots and derivatives without fixed effects

		Linear		**Quadratic**		**Cubic**	
		Solution	Derivative	Solution	Derivative	Solution	Derivative
No correction	Min	635817.82	0.5304	665143.24	0.6121	-	-
	Median	728014.43	0.5304	768870.17	0.6094	-	-
	Max	847319.02	0.5304	890096.92	0.6063	-	-
Theta = 0.5	Min			650290.01	0.6125	-	-
	Median			754118.81	0.6098	-	-
	Max			875462.87	0.6067	-	-
Theta = 0.65	Min			654747.52	0.6124	-	-
	Median			758545.73	0.6097	-	-
	Max			879854.55	0.6066	-	-
Theta = 0.80	Min			659203.71	0.6123	-	-
	Median			762971.35	0.6096	-	-
	Max			884244.99	0.6065	-	-
Theta = 0.95	Min			663658.57	0.6121	-	-
	Median			767395.67	0.6095	-	-
	Max			888634.15	0.6063	-	-

Table 5: Roots and derivatives with cohort fixed effects

[5]Only non-negative roots and roots that are not way beyond the data range were considered.

7.2 Urban areas

7.2.1 No controls (unconditional convergence)

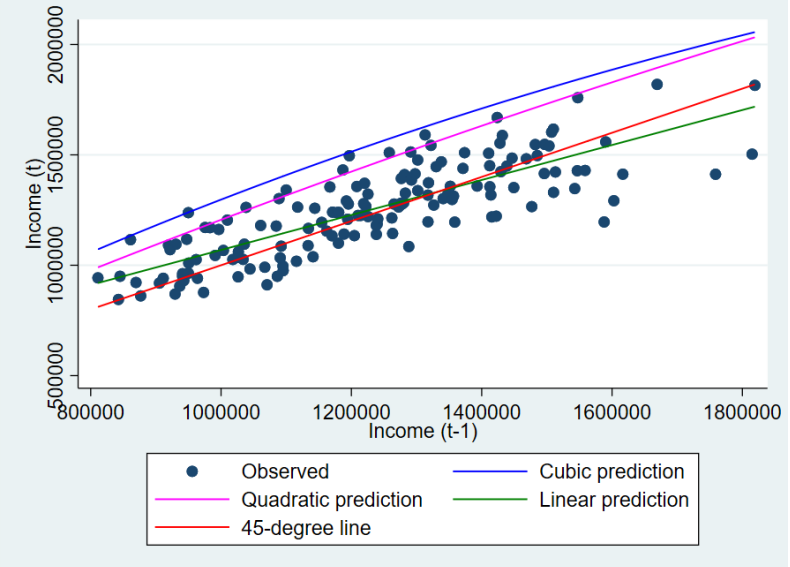
The same methodology was used for urban areas. A first approximation did not include any controls. All coefficients are statistically significant, thus there is evidence of non linearities in income. A visual representation is shown in Figure 11. The linear function crosses the 45 degree line once from above, and seemingly shows no signs of a poverty trap. The case for the quadratic and cubic models is different, as there seems to be no crossings within the data range. However, there is a crossing from below the 45 degree line for lower incomes and a crossing from above for higher incomes. This is visible from the shape of the income functions.

Table 6: Estimation for urban areas without cohort fixed effects

	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$
$\hat{\beta}_1$	0.792***	1.378***	1.757***
	(0.0458)	(0.147)	(2.704e-01)
$\hat{\beta}_2$		-1.31e-07***	-3.40e-07***
		(3.14e-08)	(1.29e-07)
$\hat{\beta}_3$			2.085e-14*
Observations	152	152	152
R-squared	0.6336	0.6802	0.6897
Number of Cohort	11	11	11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 11: Estimations without fixed effects and no bias correction



Results with constant correction are shown in Figures 12 and 13, for $\theta = 0.5$ and $\theta = 0.95$ respectively. The outcome is similar to before, but it appears that with $\theta = 0.5$ the crossings are closer to the data range.

Figure 12: Estimations without fixed effects and constant correction ($\theta = 0.5$)

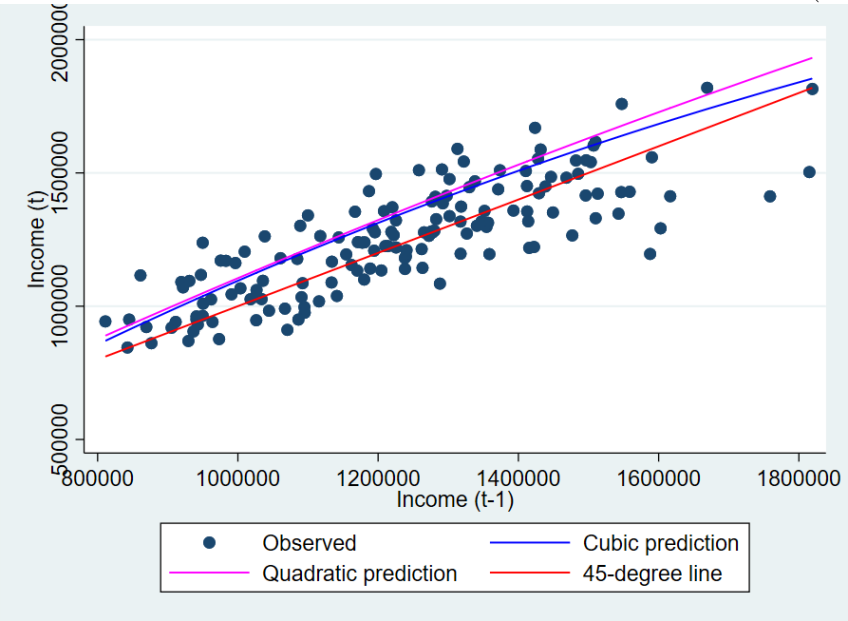
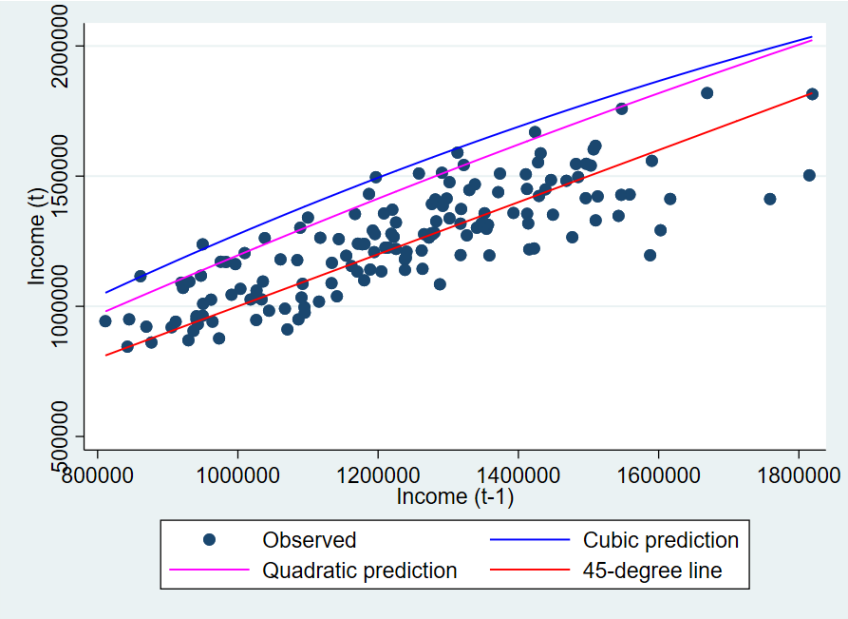


Figure 13: Estimations without fixed effects and constant correction ($\theta = 0.95$)



7.2.2 With controls (conditional convergence)

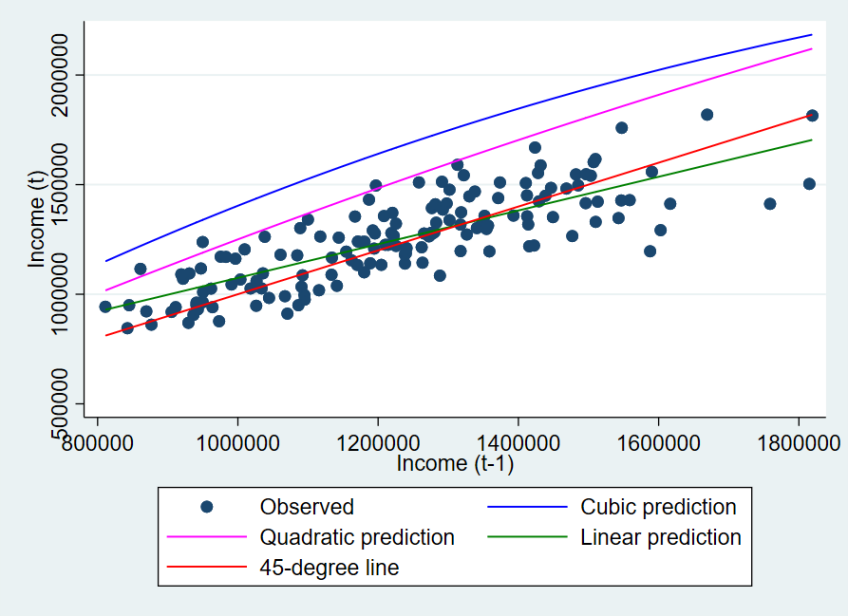
Estimations with cohort fixed effects are shown in Table 7. All coefficients are statistically significant, again pointing towards non linearities in income. The graphical representation is in Figure 14. As in the case without fixed effects, the linear prediction cuts the 45 degree line from above but there are no visible crossings for the quadratic and cubic case. They have crossings

from below the 45 degree line for lower incomes and crossings above the line for much higher incomes.

Table 7: Estimation for urban areas with cohort fixed effects

	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$
$\hat{\beta}_1$	0.769***	1.539***	2.174***
	(0.0494)	(0.172)	(3.193e-01)
$\hat{\beta}_2$		-1.69e-07***	-5.03e-07***
		(3.64e-08)	(1.47e-07)
$\hat{\beta}_3$			3.214e-14**
			(1.370e-14)
Observations	152	152	152
R-squared	0.634	0.683	0.6952
Number of Cohort	11	11	11

Figure 14: Estimation with cohort fixed effects and no constant correction



Figures 15 and 16 show the results with constant correction for $\theta = 0.5$ and $\theta = 0.95$. There are still no crossings within the data range but in the case of $\theta = 0.5$ the predictions are closer to the 45 degree line.

Figure 15: Estimations with cohort fixed effects and constant correction ($\theta = 0.5$)

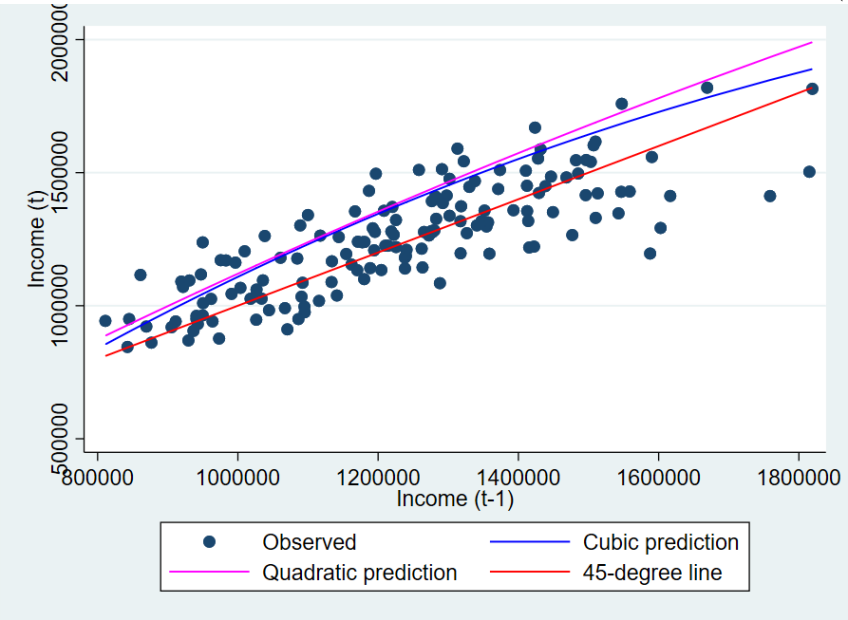
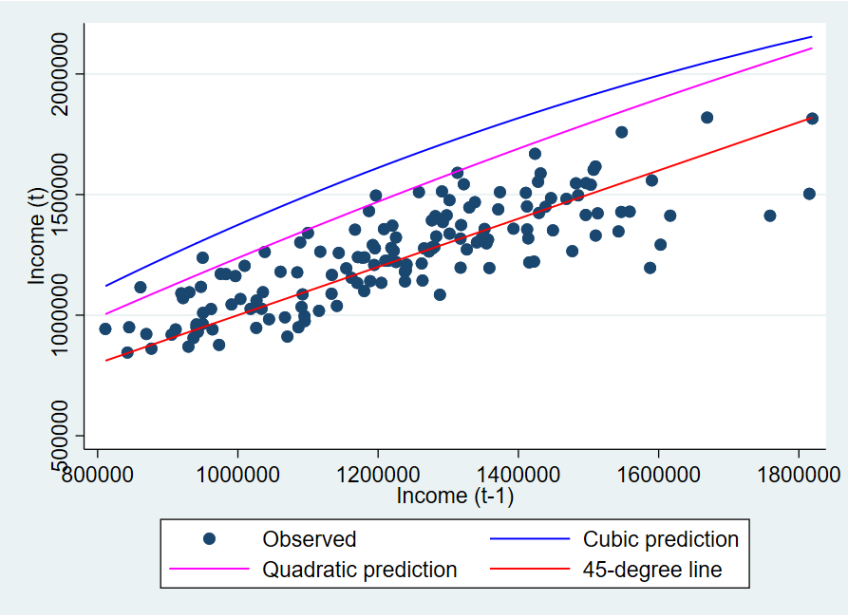


Figure 16: Estimations with cohort fixed effects and constant correction ($\theta = 0.95$)



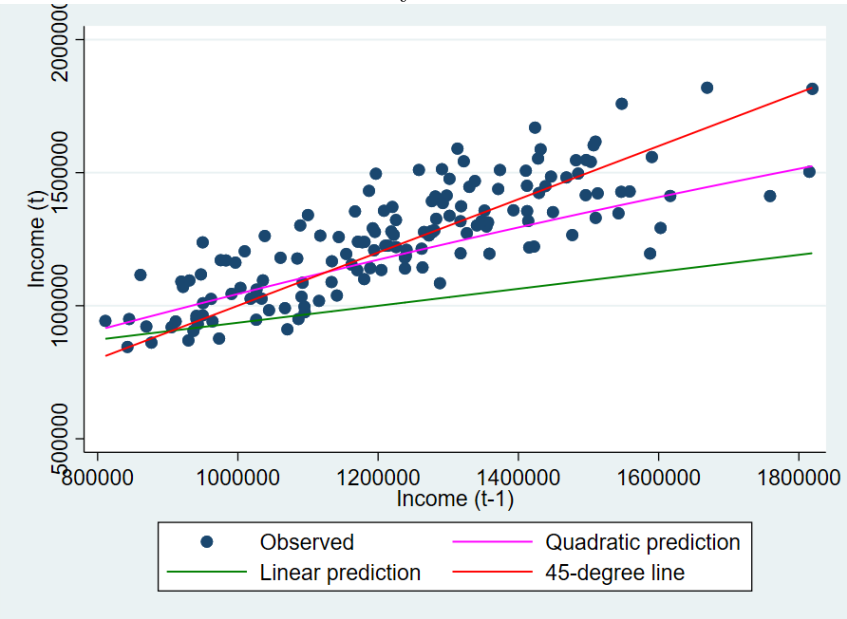
We then include both cohort and year fixed effects and display the results in Table 8. Coefficients for the linear and quadratic case are significant, but not for the cubic case. The visual representation in Figure 17 is different from the other models for urban areas. The linear prediction cuts the 45 degree line from above once, and so does the quadratic prediction. The cubic model was omitted because of its lack of statistical significance.

Table 8: Estimation with cohort and year fixed effects

	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$	$\bar{Y}_{c(t),t}$
$\hat{\beta}_1$	0.319***	0.8468***	1.052***
	(0.0833)	(2.119e-01)	(3.793e-01)
$\hat{\beta}_2$		-9.24e-08***	-1.89e-07
		(3.43e-08)	(1.52e-07)
$\hat{\beta}_3$			9.552e-15
			(1.462e-14)
Observations	152	152	152
R-squared	0.857	0.8655	0.866
Number of Cohort	11	11	11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 17: Estimation with cohort and year fixed effects and no constant correction



The outcomes with a corrected constant are in Figure 18 ($\theta = 0.5$) and Figure 19 ($\theta = 0.95$) for the quadratic model, as the cubic model was not statistically significant. They are similar to the case without correction as the quadratic prediction cuts the 45 degree line from above.

Figure 18: Estimations with fixed effects and constant correction ($\theta = 0.5$)

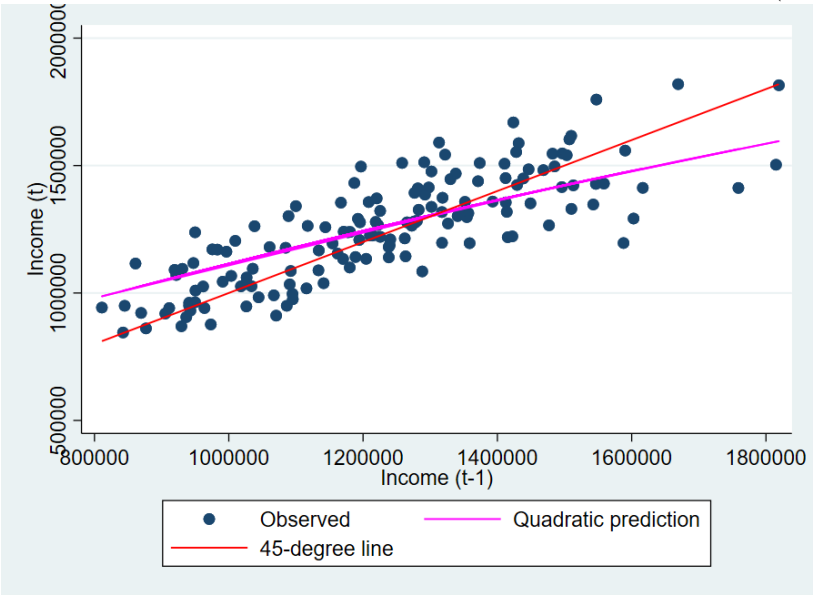
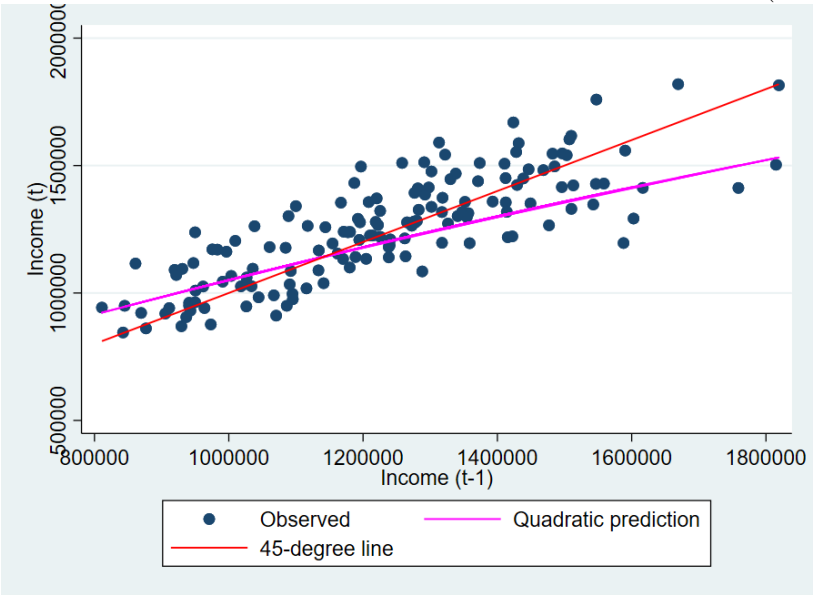


Figure 19: Estimations with fixed effects and constant correction ($\theta = 0.95$)



7.2.3 Roots and derivatives

Table 9 shows roots and derivatives for the case without fixed effects. Tables 10 (for the smaller root) and 11 (larger root) include cohort fixed effects and Table 12 is for the case with cohort and year fixed effects.[6] As it can be observed, the linear model has roots above the poverty line, and the derivative is smaller than 1, which discards a poverty trap. However, for the quadratic and cubic models with cohort fixed effects, there are roots below the observed values for income (which range from 800000 to 1800000 guaraníes) and roots above, as it was shown in the graphic representations. For all cases, the derivative for the first root is larger than 1 and the derivative for the second and larger root is smaller than 1.

[6]Negative roots and those too far away from the data range are not reported.

	Linear		Quadratic		Cubic	
	Solution	Derivative	Solution	Derivative	Solution	Derivative
No correction	1333086.346	0.7924	114188.378	1.348	203803.238	1.621
			2774078.8	0.652	2411837.097	0.4813
Theta = 0.5			444349.901	1.262	616412.103	1.361
			2443917.375	0.7381	1935999.389	0.675
Theta = 0.65			334934.068	1.291	467496.069	1.452
			2553333.108	0.709	2103748.336	0.604
Theta = 0.80			235382.329	1.317	344185.596	1.53
			2652884.847	0.683	2246007.23	0.546
Theta = 0.95			143427.795	1.341	236900.824	1.599
			2744839.381	0.659	2372357.817	0.496

Table 9: Roots and derivatives without fixed effects

		Linear		Quadratic		Cubic	
		Solution	Derivative	Solution	Derivative	Solution	Derivative
No correction	Min	1036864.65	0.769	111911.07	1.466	219265.31	1.858
	Median	1308991.88	0.769	272576.69	1.501	307894.23	1.959
	Max	1480542.86	0.769	424536.82	1.395	407995.59	1.780
Theta = 0.5	Min			399318.81	1.360	597324.86	1.562
	Median			605661.38	1.404	747153.80	1.450
	Max			820522.36	1.261	961837.18	1.296
Theta = 0.65	Min			306341.76	1.3945	464651.02	1.688
	Median			495081.33	1.435	585289.86	1.597
	Max			683456.54	1.308	735099.90	1.487
Theta = 0.80	Min			219641.50	1.427	351135.62	1.798
	Median			394655.86	1.465	454574.02	1.833
	Max			564484.39	1.348	575965.61	1.627
Theta = 0.95	Min			138096.02	1.457	250557.65	1.896
	Median			302014.40	1.492	342319.99	1.825
	Max			457906.03	1.384	446733.38	1.744

Table 10: Smaller roots and derivatives with cohort fixed effects

		Linear		Quadratic		Cubic	
		Solution	Derivative	Solution	Derivative	Solution	Derivative
No correction	Min	-	-	2762983.89	0.605	2351643.14	0.341
	Median	-	-	2914944.02	0.553	2471342.73	0.276
	Max	-	-	3075609.64	0.499	2579329.15	0.220
Theta = 0.5	Min			2366998.35	0.739	1728959.80	0.723
	Median			2581859.33	0.666	1962776.56	0.571
	Max			2788201.90	0.596	2131498.88	0.468
Theta = 0.65	Min			2504064.17	0.692	1976177.77	0.563
	Median			2692439.38	0.629	2145257.59	0.460
	Max			2881178.95	0.565	2284925.96	0.379
Theta = 0.80	Min			2623036.32	0.652	2155938.80	0.453
	Median			2792864.85	0.595	2296739.16	0.372
	Max			2967879.21	0.536	2419345.84	0.304
Theta = 0.95	Min			2729614.68	0.616	2305946.61	0.367
	Median			2885506.31	0.563	2429910.41	0.299
	Max			3049424.69	0.508	2540982.47	0.240

Table 11: Larger roots and derivatives with cohort fixed effects

The results for urban areas vary by model. With a linear estimation, there is no indication of a poverty trap in any variation. For the quadratic and cubic models without fixed effects and with cohort fixed effects, we can see that there is a crossing of the income function with the 45 degree line from below, as portrayed by the derivative being larger than 1. The consequence of this is an unstable equilibrium. If the household finds itself at an income level below the equilibrium, it will get trapped as income in t will be smaller than income in $t-1$. There are also greater crossing with a derivative smaller than 1, indicating the income function cuts the 45 degree line again from above.

As was shown in Figures 17, 18 and 19, when we add both cohort and year fixed effects there is one crossing from above (derivative smaller than 1) for the linear and quadratic models (cubic model was not significant). This is consistent with no poverty trap.

		Linear		Quadratic		Cubic	
		Solution	Derivative	Solution	Derivative	Solution	Derivative
No correction	Min	783975.53	0.319	756423.99	0.707	-	-
	Median	860600.35	0.319	1045194.03	0.654	-	-
	Max	1072249.19	0.319	1382538.47	0.591	-	-
Theta = 0.5	Min			983537.96	0.665	-	-
	Median			1240862.73	0.617	-	-
	Max			1550629.01	0.560	-	-
Theta = 0.65	Min			916625.03	0.677	-	-
	Median			1182527.67	0.628	-	-
	Max			1500065.29	0.570	-	-
Theta = 0.80	Min			850268.31	0.690	-	-
	Median			1125220.50	0.639	-	-
	Max			1450754.01	0.579	-	-
Theta = 0.95	Min			781179.40	0.702	-	-
	Median			1066181.31	0.650	-	-
	Max			1400352.31	0.588	-	-

Table 12: Roots and derivatives with cohort and year fixed effects

8 Conclusions

The aim of this work was to study the existence of poverty traps in Paraguay's urban and rural areas. We use pseudo panels in order to deal with the problems that are present with the use of traditional panels.

Although we uncovered the existence of non linearities in income dynamics for both urban and rural areas, results for poverty traps vary between the regions. For rural areas, there was no evidence of any kind of poverty trap described as in our model. This held for every specification.

However, we observed a different outcome for urban areas. For quadratic and cubic models without fixed effects and with cohort fixed effects, a low unstable equilibrium was found that is consistent with the existence of a poverty trap. This could be surprising as average incomes are greater for urban than rural areas, but the detection of the trap is not about the values of income, but about the estimated income dynamics that relate income today to its value from the previous period. The unstable equilibrium found for urban areas was below the data range of the observed income, but it could indicate that if a household were to fall below it, it would be unable to come out. We have a self reinforcing mechanism that prevents mobility. Still, the non linear income dynamics portray another equilibrium, which is higher and stable. If a shock occurs and households manage to reach it or surpass it, according to our model they will remain out of poverty. These results only change for the quadratic prediction with cohort and year fixed effects. As the aim of this project was not related to the underlying mechanisms behind poverty traps, we cannot be sure which model is more effective.

These findings are the first of their kind for Paraguay. Few works on the subject have been made before for the country, and none that follow the same methodology. The existence of a poverty trap emphasizes the significant role of public policy, not only in safeguarding households from descending into such conditions but also in facilitating their escape should they become trapped. However, we believe further research would be beneficial, especially on the matter of possible mechanisms behind a poverty trap, since Paraguay remains an understudied case.

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10 Appendix

10.1 η demonstration

$$\eta_{i,t} = \mu_{i,t} + \text{ measurement error}$$

$$\eta_{i,t} = \mu_{i,t} + \varepsilon_{i,t} + \beta_1 Y^*_{i,t-1} + \beta_2 (Y^*_{i,t-1})^2 + \beta_3 (Y^*_{i,t-1})^3 + \alpha_i - [\beta_1 Y_{i,t-1} + \beta_2 Y^2_{i,t-1} + \beta_3 Y^3_{i,t-1} + \alpha_i]$$

Where $Y_{i,t} = Y^*_{i,t} + \varepsilon_{i,t}$, so $Y^*_{i,t} = Y_{i,t} - \varepsilon_{i,t}$.

$$\eta_{i,t} = \mu_{i,t} + \varepsilon_{i,t} + \beta_1 (Y_{i,t-1} - \varepsilon_{i,t-1}) + \beta_2 (Y_{i,t-1} - \varepsilon_{i,t-1})^2 + \beta_3 (Y_{i,t-1} - \varepsilon_{i,t-1})^3 - \beta_1 Y_{i,t-1} - \beta_2 Y^2_{i,t-1} - \beta_3 Y^3_{i,t-1}$$

$$\eta_{i,t} = \mu_{i,t} + \varepsilon_{i,t} + \beta_1 [Y_{i,t-1} - Y_{i,t-1} + \varepsilon_{i,t-1}] + \beta_2 [(Y - \varepsilon_{i,t-1})^2 - Y^2] + \beta_3 [(Y_{i,t-1} - \varepsilon_{i,t-1})^3 - Y^3]$$

$$\eta_{i,t} = \mu_{i,t} + \varepsilon_{i,t} - \beta_1 \cdot \varepsilon_{i,t-1} + \beta_2 [-2 Y_{i,t-1} \varepsilon_{i,t-1} + \varepsilon^2_{i,t-1}]$$
$$+ \beta_3 [-2 Y^2 \varepsilon_{i,t-1} + \varepsilon^2_{i,t-1} Y_{i,t-1} - \varepsilon_{i,t-1} Y^2_{i,t-1} + 2 Y_{i,t-1} \varepsilon^2_{i,t-1} - \varepsilon^3_{i,t-1}]$$

$$\eta_{i,t} = \mu_{i,t} + \varepsilon_{i,t} - \varepsilon_{i,t-1} (\beta_1 + 2\beta_2 Y_{i,t-1} + 3\beta_3 Y^2_{i,t-1}) + \varepsilon^2_{i,t-1} (\beta_2 + 3\beta_3 Y_{i,t-1}) - \varepsilon^3_{i,t-1} \beta_3$$

10.2 Average monthly income per cohort

Figure 20: Average monthly family income per capita by cohort for rural areas

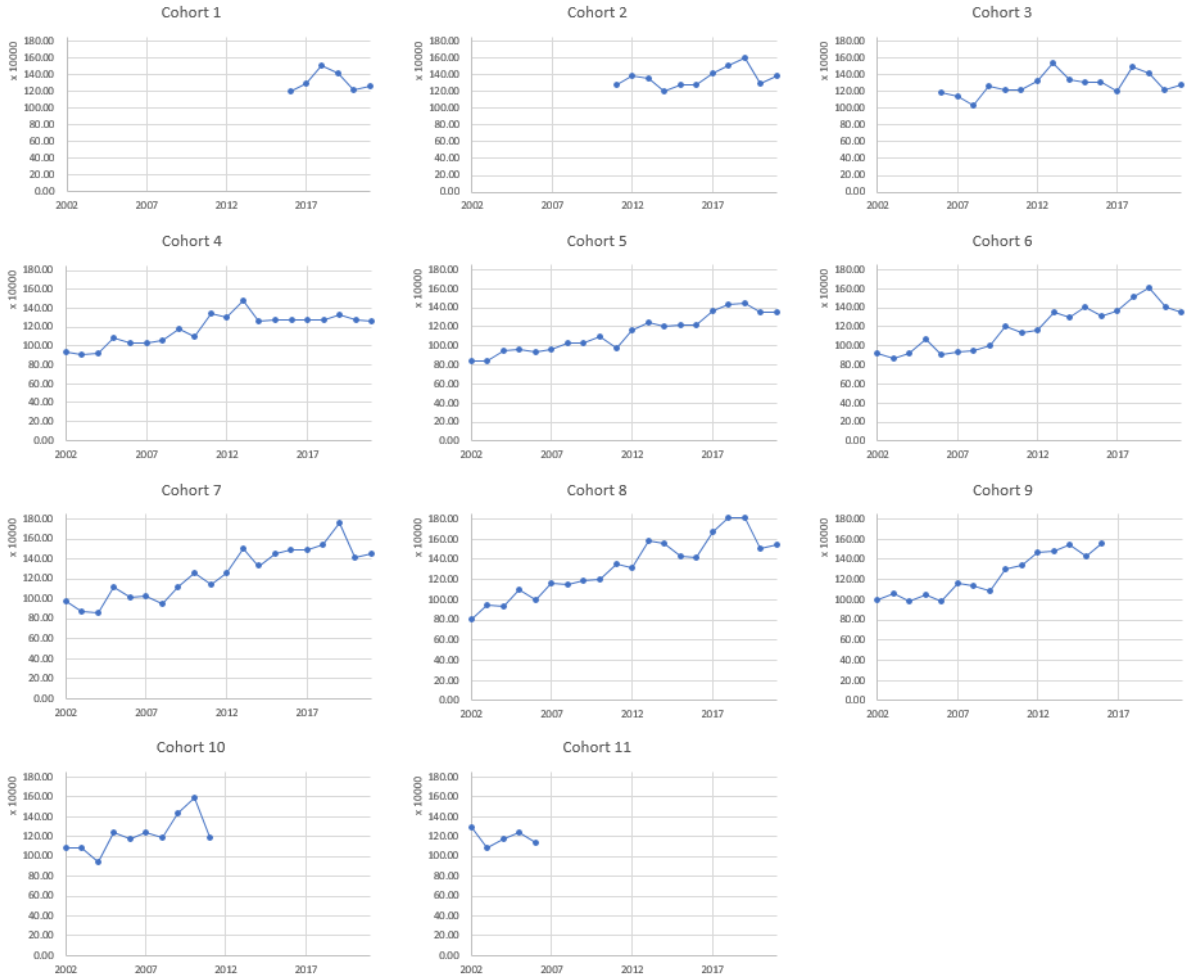

Figure 21: Average monthly family income per capita by cohort for urban areas