CAF - WORKING PAPER #2022/06
First version: April 25, 2022
This version: April 25, 2022

Intergenerational earnings mobility and macroeconomic shocks: Evidence based on administrative records

Martín Leites[1] | Tatiana Pérez[2] | Xavier Ramos[3] | Sofía Santín[4] | Joan Vilá[5]

[1]IECON-UDELAR and EQUALITAS.
martin.leites@fcea.edu.uy
[2]IECON-UDELAR.
tatiana.perez@fcea.edu.uy
[3]Universitat Autònoma de Barcelona, IZA, and EQUALITAS.
xavi.ramos@uab.cat
[4]IECON-UDELAR.
sofia.santin@fcea.edu.uy
[5]IECON-UDELAR.
joan.vila@fcea.edu.uy

This paper provides novel evidence on trends in intergenerational earnings mobility in a developing country and explores some transmission mechanisms associated with the characteristics of the labor market. Using a novel social security records database for Uruguay, we study the intergenerational earning ranking association from cohorts between 1966-1983. To explore intergenerational transmission mechanisms, we exploit the arguably exogenous variation induced by the 2002 macroeconomic crisis to analyse the impact of parental displacement from jobs on their children's labor trajectories. First, we focus on the effect of the crisis on parents' labor market performance. In a second stage, we use this information as a shock to identify the effect on children outcomes of a parent's employment shock. Results suggest (i) heterogeneity on the degree of intergenerational earning mobility across birth cohorts; (ii) weak evidence of downward trend in relative mobility, (iii) intergenerational transmission of the shock produced by the 2002 crisis.

KEYWORDS
Intergenerational earning mobility, macroeconomic shock, unemployment, intergenerational transmission, cohorts

CAF - DOCUMENTO DE TRABAJO #2022/06

Primera versión: 25 de abril de 2022

Esta versión: 25 de abril de 2022

Movilidad intergeneracional de ingresos y shocks macroeconómicos: Evidencia basada en registros administrativos

Martín Leites[1] | **Tatiana Pérez**[2] | **Xavier Ramos**[3] | **Sofía Santín**[4] | **Joan Vilá**[5]

[1]IECON-UDELAR and EQUALITAS.
martin.leites@fcea.edu.uy

[2]IECON-UDELAR.
tatiana.perez@fcea.edu.uy

[3]Universitat Autònoma de Barcelona, IZA, and EQUALITAS.
xavi.ramos@uab.cat

[4]IECON-UDELAR.
sofia.santin@fcea.edu.uy

[5]IECON-UDELAR.
joan.vila@fcea.edu.uy

Este trabajo proporciona evidencia novedosa sobre la evolución del grado de movilidad intergeneracional de ingresos en un país en desarrollo y explora algunos mecanismos de transmisión asociados con las características del mercado laboral. Usando una nueva base de datos de registros de seguridad social para Uruguay, estudiamos la asociación intergeneracional en el ranking de ingresos laborales formales entre las cohortes de 1966 a 1983. Para explorar los mecanismos de transmisión intergeneracional, explotamos la variación potencialmente exógena inducida por la crisis macroeconómica de 2002 a fin de analizar el impacto de la pérdida de empleo de los padres en las trayectorias laborales de sus hijos. Primero, nos enfocamos en el efecto de la crisis en el desempeño del mercado laboral de los padres. En una segunda etapa, usamos esta información como un shock para identificar el efecto en los desempeños de la segunda generación. Los resultados sugieren una (i) heterogeneidad en el grado de movilidad salarial intergeneracional entre las cohortes de nacimiento; (ii) débil evidencia de una tendencia a la baja en la movilidad relativa; (iii) transmisión intergeneracional negativa y significativa del shock producido por la crisis de 2002.

KEYWORDS

Movilidad intergeneracional de ingresos, shocks macroeconómicos, desempleo, transmisión intergeneracional, cohortes

1 | INTRODUCTION

We provide novel evidence on trends in intergenerational earnings mobility and some mechanism behind the inequality persistence in the labor market for a developing country using administrative earnings records from several social security databases. More precisely, first, we estimate the intergenerational income ranking association (IRA) of matched parents and their offspring, based on a representative sample of Uruguayan descendants from cohorts between 1966-1983. Second, we provide some additional measures of intergenerational persistence and we explore whether there were changes over time in the directional mobility of the analyzed cohorts. Finally, we explore some transmission mechanisms associated with the functioning of the labor market. In particular, we exploit the arguably exogenous variation induced by the 2002 macroeconomic crisis to analyse the impact of parental displacement on their children's labor trajectories. We seek to identify the impact that the unfavourable employment shock experienced by parents in 2002 may have had on the employment and earnings of the next generation.

It is well established in the literature that the socioeconomic status of children is to some extent correlated with the performance of their parents or the characteristics of their household of birth. However, there still is some controversy about the magnitude of this relationship (How much?) and whether there are differences between regions (Where is the mobility?), its recent trend (Were societies less mobile in the past?), and the mechanisms behind intergenerational mobility (How?).

The intergenerational income mobility literature employs several measures and provides evidence on the relationship between parents and children's lifetime income, and suggests news arguments to explain the persistence of income inequality in the long term and between families (Jäntti and Jenkins, 2015). This literature examines data mostly from industrialized, rich countries (notably Canada, the Nordic countries, the UK, and the US), and makes increasing use of administrative records (Corak and Heisz, 1999; Chetty et al., 2014b,a; Björklund et al., 2012, 2009; Mitnik et al., 2015a; Munk et al., 2016; Mazumder, 2005). Administrative records have been found to yield more precise estimates of intergenerational mobility and to mitigate the classical problems of measurement error, attenuation, and life-cycle biases (Nybom and Stuhler, 2017; Mitnik et al., 2015a; Chetty et al., 2014a; Jäntti and Jenkins, 2015).

Previous evidence from developing countries, and Latin America in particular, is entirely based on cross-section survey data covering short periods of time, and the use of two-sample instrumental variables methods suggested by Bjorklund and Jantti (1997), such as Dunn (2007); Jiménez (2018). However, recent papers for Chile and Uruguay employ administrative records to measure intergenerational income mobility (Leites et al., 2020, 2021; Díaz et al., 2021). Recent estimates for Uruguay provide evidence on intergenerational income mobility based on administrative records from the Tax authority but their sample period goes from 2009 to 2016 and does not cover the 2002 economic crisis we exploit (Leites et al., 2020). [1]

Piketty (2000), Solon (2002), and Bourguignon et al. (2007) review the different mechanisms that the economic literature has suggested to explain the degree of income persistence across generations, considering genetic, demographic, behavioral, institutional, sociocultural, political and economic factors. This review suggests three issues. First, how relevant are these mechanisms to explain intergenerational income transmission as a key issue to

[1] Another group of papers studies educational mobility for Latin American countries, which could indirectly provide a proxy of income mobility. Daude and Robano (2015) and Neidhöfer et al. (2018) use information from *Latinobarómetro* for a group of Latin American countries and find a relatively high persistence of educational attainments. Furthermore, educational mobility varies across Latin American countries.

public policy recommendations. Second, it suggests that the conventional intergenerational earnings measures confound several parameters. Finally, the standard parent-child regression is a reduced form that typically measures the extent of intergenerational mobility or persistence but does not necessarily have a causal interpretation. As a result, although there is now more evidence on the levels of intergenerational income mobility -mainly for developed countries-, the relevance of the alternative mechanisms behind intergenerational mobility are not fully understood. In this sense, recent empirical papers have begun to unpack the mechanisms behind the intergenerational earnings correlation.

In this paper, we investigate whether the macroeconomic conditions of the labor market are an intergenerational transmission mechanism. Previous scholars have documented that negative shocks in the labor market -e.g. employment job separations- have persistent and large effects on worker earnings and labor trajectories. (Jacobson et al., 1993; Seim, 2019; Amarante et al., 2014). The size and persistence of these effects are associated with the worker's characteristics, the labor market institutions, and the macroeconomic conditions at the time when the worker suffers the adverse labor market shock (Verho, 2017; Couch and Placzek, 2010).

The negative effects of these adverse shocks on worker trajectories could be transmitted to other members of the household. In particular, they can have consequences on the performance of the children, in terms of their entry, trajectory, and income in the labor market (Bratberg et al., 2008; Seim, 2019; Huttunen and Riukula, 2019; Oreopoulos et al., 2008). Adverse shocks may have consequences on children's trajectories and intergenerational income mobility through several mechanisms. They may affect directly family resources and parental environment, which are key factors to produce children cognitive and non-cognitive skills required for success at school and the labor market (Carneiro and Heckman, 2002). In an economy with credit market imperfections, negative income shocks generate credit constraints which may likely restrict poor parents' investments in their children's human capital (Carneiro and Heckman, 2002; Piketty, 2000; Couch and Placzek, 1997). Adverse shocks may have intergenerational consequences even if they solely affect the employment status of the parents and do not affect their permanent income. Previous evidence suggests that part of the persistence of income between parents and offspring is explained by the transmission of employers, networks, assets, specific human capital, and professions (Corak and Piraino, 2010; Kramarz and Skans, 2014; Chen et al., 2017). The relevance of these alternative channels depends in part on the moment of the life cycle that the child is when the parent faces the shock, the parent's characteristics, and the previous situation of the children's household. For example, it is known that cognitive ability is formed at relatively early stages of the life cycle and it becomes less malleable as children age.

Previous research explores the effect of unemployment on the permanent income of children for developed countries but, to the best of our knowledge, there is no evidence about how an adverse macroeconomic event affects the level of intergenerational transmission of income for a developing country. The availability of administrative records linking parents and children in Uruguay, with longitudinal information on their labor income during their adulthood generates an opportunity to contribute to closing this gap. This paper provides precise measurements of intergenerational earning mobility for a period covering the 2002 crisis and assesses whether the adverse labor market consequences of the crisis were transmitted to the next generation.

To fill these gaps in the literature, we seek to contribute evidence to address the following three research questions.

1. How has the level of intergenerational mobility of formal labor earnings evolved in Uruguay between 1996 and 2015?

2. How did the economic crisis experienced in Uruguay in 2002 and its consequences on parents' employment affect their children's labor trajectories?
3. To what extent did the economic recession and social crisis faced by Uruguay in 2002 affect the magnitude of the intergenerational transmission of earnings?

The first research question focuses on the evolution of the degree of mobility in Uruguay for the cohorts born between 1966 and 1983, exploiting the availability of administrative records over 20 years. We work with a sample that contains more than 100,000 pairs with income/earnings information based on tax records for the period 2009-2016. Under certain assumptions, the large size and the high-quality dataset allow us to obtain precise estimates of the intergenerational transmission of income ranking.

Our empirical strategy relies on the analyses of two groups of cohorts 1966-1981 (aged 30-34) and 1968-1983 (aged 28-32).[2] First, we use alternative rank-based measures to explore the average mobility by cohort. We mainly focus on relative mobility measures, but also, we follow Chetty et al. (2014b) to address changes on absolute mobility. Then we employ non-parametric strategies to explore the presence of non-linearities in the relationship between parental and offspring's income and to explore the direction of the movements. Third, we estimate transition probability for each cohort to analyse the evolution of the directional mobility and the intergenerational persistence.

This analysis provides a big picture of the intergenerational earning mobility in Uruguay. Our measures of mobility incorporates a subgroup of cohorts which have faced the effects of the 2002 crisis, which allows us to provide a first descriptive analysis whether the degree of mobility is related with the macroeconomic shock. To advance in this sense, we define the cohorts with alternative age ranges, which allows to explore if the moment in the child' life cycle at which the shock occurred have some relevance to measure the cohort's intergenerational mobility.

The second and third questions contribute to understand how parents' displacements that result from the 2002 crisis affect the trajectories of their children and the intergenerational persistence of inequality. In 2002 the Uruguayan economy experienced its most acute economic crisis. As a result, workers experienced real earnings losses and the unemployment rate reached 17 % in annual terms (Amarante et al., 2013). We use parent's displacement as a source of exogenous variation in family resources to explore its effect on the next generation. In the first stage, we focus on the effect of the crisis on workers' labor market performance. In this case, we use methods developed in the displacement literature to explore whether displacements have an effect on family resources. We estimate a panel event-study to assess the effect of the 2002 crisis on parent's generation.

In a second stage, we use this information as a shock in order to identify the effect on children's outcomes of a parent's employment shock. Applying similar approaches as Oreopoulos et al. (2008) we evaluate the incidence of the job separation that parents experienced in 2002 on the performance of their children. We look at childrens' short-term earnings and also at their permanent income. To understand the different channels that could operate in the intergenerational transmission, we measure the effect on different cohorts of children. This strategy allows heterogeneity across the life cycle of the children regarding the timing of the shock of the 2002 crisis. Finally, this allows us to explore whether the crisis has affected the intergenerational earning transmission.

We find a weak decrease in relative mobility for the analyzed cohorts. Concerning absolute mobility, the data seem to be indicating higher mobility for the later cohorts. We

[2] Our baseline results are based on the analyses of two groups of cohorts 1966-1981 (aged 30-34) and 1968-1983 (aged 28-30). In order to address some specific issues and as robust check, we consider a third group of cohorts 1972-1987 (aged 24-28).

find a consistent pattern to these results when incorporating the life cycle, the sex of the children, and alternative criteria to define the income of the parents.

Regarding the effect of the crisis on intergenerational mobility levels, we first find that the individuals who experienced the negative shock show larger reductions in their wages, particularly in the first year after the shock. Additionally, we find that the effect on second generations is negative, and that it depends on the position of the parents and the age of the children at the moment of the shock. The results suggest that the effects in the second generation are greater for those children whose parents are located in the middle and upper part of the income distribution. This could be consistent with the fact that the adverse shock faced by parents decreases the social capital, networks and specific capital of families. But also, this could be explained by a mechanical effect due to the fact that the relative mobility is higher in the lower part of the distribution. Finally, the results suggest that the IRA is slightly lower for families that faced adverse shock.

This study contributes to the literature on the long-term evolution of the intergenerational mobility based on administrative tax record. There is a recent group of papers that use administrative records to explore the long-term trends of intergenerational mobility (they combine additional data sources if needed). Manduca et al. (2020) provide an absolute measure of income mobility for the 1960-1987 birth cohorts in eight countries in North America and Europe, and conclude that absolute mobility varied significantly across countries. There is also an increasing use of administrative records to obtain trends in alternatives measures of intergenerational mobility at country level. This evidence had been concentrated in rich countries as US (Chetty et al., 2017, 2014b) and Norway (Bratberg et al., 2005). Results for US depends on the mobility measure considered and suggest a fall in absolute mobility and a relatively stable trend in terms of relative mobility. For Norway, (Bratberg et al., 2005) explore the cohorts 1950, 1955, 1960 and 1965, and they found increased mobility over time for sons. Their results suggest that the mobility fall between both cohorts. Previous papers explore the changes on intergenerational mobility between a group of cohorts based on survey data, as is the case of Davis and Mazumder (2020) for US and Blanden et al. (2005) for Britain. The former uses National Longitudinal Surveys to compares the cohorts born between 1942 and 1953 with respect to those born between 1957 and 1964. They conclude that that relative mobility fell while absolute mobility remained relatively stable. Finally, Blanden et al. (2005) uses two surveys (the National Child Development Study and the British Cohort Survey) to compare the intergenerational income mobility between the 1958 birth cohort and the 1970 birth cohort. Three main messages emerge from this literature: (i) the trends of intergenerational mobility varies between countries; (ii) results regarding trends are very sensitive to the measure of intergenerational mobility that is considered (e.g. absolute vs relative); (iii) to assess the changes on intergenerational mobility in the long term, it could be necessary to consider changes on income inequality over time.

Our contribution to this literature is that we are the first to be able to provide a set of mobility measures based on administration records data for a developing country, and to do so with relatively large samples and 16 births cohorts. This allows use to explore the evolution of earning mobility in a country where macroeconomic volatility affect the labor market dynamic and the worker performance. We show that the intergenerational earning mobility in Uruguay remains relatively stable or declines slightly.

Second, this study contributes to literature on the role of adverse macroeconomic shock in the labor market on the degree of intergenerational transmission of earning (Bratberg et al., 2008; Oreopoulos et al., 2008). Bratberg et al. (2008) use displacement of fathers as an exogenous earnings shock in Norway to identify whether the fall in family income have an adverse effect on offspring's economic outcome. Fathers' displacement have a negative effect on their earnings, but the authors do not find significant effects on offspring.Oreopoulos et al.

(2008) address the same question for Canada and using administrative data, but they use the variation induced by firm closures as exogenous shock and explore the intergenerational effects of father displacement on children economic outcomes. They found that offspring whose fathers were displaced face a reduction of 9 % in annual earnings compared to similar children whose fathers did not experience an adverse shock. The effect is mainly driven by the trajectories of children whose origin was at the bottom of the income distribution.

We contribute to this literature with new evidence about the impact of an unfavourable employment shock experienced by parents on current and permanent earnings of the offspring. Our results confirm the effect of the employment shock in the first generation and suggest a transmission to the second generation. We find that parent displacement due to the macroeconomic shock has a negative effects on children's permanent earning compared to similar children whose fathers did not experience displacement from their jobs. Unlike previous papers, we find a statistically significant negative effect of parents' displacement on the intergenerational ranking association. The IRA coefficient decrease is mainly driven by the effect of the shock on children whose origin was at the middle and the top of the income distribution, which could be related with loses in specific human capital, destruction of social capital and networks. This evidence is particularly relevant for a developing country, where inequality and poverty are higher than the levels of the countries addressed in the previous paper, and where the labor market institutions, size of informal sectors, welfare state system are very different.

Finally, the contributions of this paper are relevant for public policy, considering that it addresses a developing country where macroeconomic volatility and levels of inequality play a prominent role (Breen and García-Peñalosa, 2005; Aghion et al., 1999). Evidence found on the role of the macroeconomic shock on the intergenerational earning transmission provides an additional perspective on the long term effect of macroeconomic shock on individual well-being and income inequality. Also, it could be useful to understand the potential long-term adverse effect of other socioeconomic crisis, like the impact of the sanitary crisis of COVID-19. Evidence on the questions raised could provide new arguments for more active interventions in times of recession and, more generally, redistributive policies that reduce persistent poverty.

The paper is structured as follows. The next section presents the empirical strategy. It describes the data sources, the samples, our variables and the econometric model. Section 4 presents our main results on the long-term intergenerational earning mobility, and section 5 presents the evidence about the effect of the 2002 crisis on intergenerational transmission. Finally, section 6 includes some final comments.

2 | EMPIRICAL STRATEGY

2.1 | Data source

We match two sources of administrative micro-data from the main Uruguayan social security institution (Banco de Prevision Social, BPS), to estimate the intergenerational mobility in Uruguay: a database that provides the information about the link between parents and their offspring, and a dataset of the administrative records of the workers' earnings histories and unemployment insurance benefits. These two data sources were especially linked for this work using a unique personal identifier (*Cédula de Identidad*), which is not available to prevent access to the identity of individuals.

The information to link parents and sons comes from a wide set of social programs implemented by BPS: health coverage, conditional cash transfers, and other social benefits.[3]

[3]Benefits included are those provided by the *BPS*, the main public institution that regulates social benefits.

This database covers the period 1980-2018 and includes about 3 million individuals, with more than 55 % composed of sons or daughters, and a larger presence of mothers than fathers.[4]

The information of child and parents' earnings is based on the workers' earnings histories, which is the dataset of administrative records of contribution to social security. This dataset includes monthly earnings for more than 1.500.000 formal workers, from January 1996 to April 2015.[5] The advantages of using these administrative records to explore workers' labor market trajectories in Uruguay have been documented by previous research, which has studied different performances (Amarante et al., 2014, 2013; Querejeta and Bucheli, 2021).

Previous studies emphasize that the use of longitudinal information based on administrative records to measure intergenerational mobility offers some advantages. First, it mitigates the problems of biases associated with measurement errors and life-cycle. Second, having a large number of observations allows the use of more flexible specifications that offer greater precision to approximate the functional form of this relationship. A usual limitation of this type of database is the scarce availability of variables. The dataset contains information on labor earning, entries in unemployment, sickness and maternity insurance, functional relationship, date of entry, and exit from the company. Regarding the characteristics of the companies, there is information about the creation date, closing date, and the number of workers. Finally, regarding the characteristics of the worker, the base includes sex and date of birth. Information on workers' educational attainments, occupation, and other personal or family characteristics is not available.

One of the major problems in our data involves the impossibility of identifying whether workers' lack of contribution to social security is due to informal work. The intergenerational earning measures included in this paper only consider information about workers' formal earning. The informal sector in Uruguay is relatively smaller in relation to the Latin American average, but still represents almost a third part of the labor market. This level is similar to some developed European countries. In 2016, the informal sector was close to 25 % of all workers and 12 % of wage earners. The incidence of informal work activities is higher among younger workers and for women (Leites et al., 2018).

In sections 2.3 and 2.4 we describe the strategies used to mitigate the potential problems related to informal earning and the measurement of intergenerational earning mobility.

2.2 | Sample

We construct our sample by merging earning data for the years 1996-2015 with the database that identifies the parent-child links. A parent-child pair is considered complete when it has at least one father/mother that is linked with their child. In most of the cases, only one of the parents is identified. As a result, from the universe of formal workers, we have a sample of more than 232,000 parent-child links (approx. 464,000 workers).

To select our final sample, we apply a number of necessary criteria to define permanent income and identify the children's cohorts. First, our samples consist of father-son pairs, with sons' earnings measured from age 28 to age 34 and parents' earnings measured from

Until 2008, before a major health system reform, most of these policies were linked to formal employment. This database was used by Leites, et al (2021) to measure intergenerational income mobility. In this case, BPS's database with information about family ties was linked with tax micro-data records from the tax agency.

[4] The total population of Uruguay in the period was approximately 3.5 million people, so this sample includes a large share of the population. It includes all individuals who were beneficiaries of the programs managed by the BPS at least once during the covered period. However, it must be taken into account that part of these individuals may not have formal income.

[5] To present the full year, the observed earnings for 2015 were annualized by repeating them four times.

age 45 to age 65. Previous papers suggest that earnings stabilize once workers have reached the age of around 30. (Chetty et al., 2014b). We select those children and parents with at least one positive earning record at some point in the period covered by the databases.

Second, in the case of children, we use two alternative definitions of the cohort which establishes our baseline samples. On one hand, we consider those children that we can observe almost 5 years in our administrative records and have at least one positive earning when they are at the ages of 30-34. In this case, we construct a sample of 100,850 children in the 1966-81 birth cohorts. On the other hand, we consider those children that we can observe almost 5 years in our administrative records and have at least one positive earning when they are at the ages of 28-32. In this case, we construct a sample of 131,895 children in the 1968-83 birth cohorts.

A potential limitation of the sample built from the combination of these administrative records is the identification of the parent-sons pairs, that come from specific policies included in social security records. With this aim, we make a brief analysis of the degree of representativeness of our sample of children regarding the universe of administrative records, particularly the level of earning, the main variable of our analysis.

To advance in this sense, the distribution of the sample of 30-year-old children in each of the birth cohorts (sample to be used in the estimates) is compared with the universe of individuals of that age with formal earning in each year. The Total column of Table A.1 presents the absolute number of children with 30 years that we can identify in each year, which will be the base information for the construction of the cohorts. The rows reflect for each year how our sample of children is distributed with respect to the deciles of the reference formal income distribution.

Figure 1 summarises the uptake of the children that are part of our sample by cohort and income deciles. First, note that the 30-year-old children selected in our sample increase their participation with respect to the universe of workers with formal earning of the same age in the most recent years. Our baseline sample includes a decreasing number of observations for the older cohorts. Despite this, there are still more than 1,000 children at births-cohorts 1966 (they are 30 years old in 1996). However, in all cohorts, uptake along the reference distribution is relatively balanced for each year, indicating that the sample of children adequately represents the formal income distribution of their generation.

Additionally, as we describe in the next section, our ranking-based measures consider alternatively as reference the global earnings distribution and the sample earnings distribution. These alternative definitions of percentiles allow us to explore the sensitivity of our results to potential problems of representativeness of the samples.

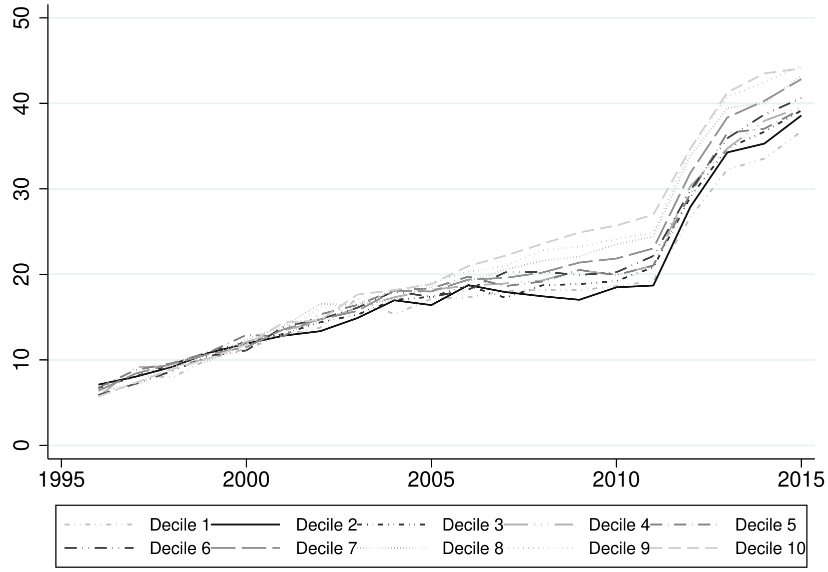


FIGURA 1 Comparison of samples used to the construction of the cohorts between 1966 and 1981 (aged 30-34 years old) with universe of tax records (percentage of the sample of children by percentile of formal income for each year). Shares are estimated when children are 32 years old. *Source:* Own elaboration based on social security records.

Another potential drawback of our strategy for the identification of the parent-sons pairs is the sex composition of the sample of the generation of parents. For the older birth cohorts, the sample of parents made up mostly of women, but the composition is balanced for the more recent cohorts. The potential implications of this issue will be considered when we interpret our results regarding intergenerational earning mobility. To address this problem, we performed regressions according to the sex of the parents. In this case, our estimates are based on three age-grouped cohorts in order to have a sufficient number of observations.

We incorporate an additional sample of children to address the effect of the economic crisis in 2002 on intergenerational earnings mobility. For this purpose, we consider younger children to explore the effect during different life-cycle stages. We include those children that we can observe almost 5 years in our administrative records and have at least one positive earning when they are at the ages of 24-28. In this case, we construct a sample of 203.668 children in the 1972-87 birth cohorts.

Another relevant aspect of the identification strategy that will be presented below is to have information on the performance of the children in the environment of the 2002 crisis. For that year we have approximately 25,500 children between the ages of 24 and 28 whose parents report positive income, reaching more than 98,000 children in 2012, with the same characteristics.[6] Additionally, the database has an average per year of approximately 2,700 children with 30 years of age between 1996 and 2002, this average being almost 9,800 for the rest of the period.[7] The size of these samples is comparable to that used by antecedents applying similar identification strategies.

Finally, Table 1 shows the number of observations available to address the effects of the 2002 crisis on children's labor trajectories. In this case, the number of parent-child pairs is

[6]Note that the age range of the children presented in the Figure 2 is broader and does not coincide with the one used to define the cohorts. However, it provides an approximation of the families that may have been affected by the shock through parental unemployment.

[7]These differences can be explained by the life cycle and increased formality throughout the period.

identified depending on the age bracket in which the children were at the time of the 2002 crisis: 18 to 24 years old, or 28 to 32 years old, and 30 to 34 years old.[8] For these pairs it is possible to identify those who suffered an unemployment event (sending to Unemployment Insurance) year by year, from the total sample. The number of ties with children is higher in the younger bracket, varying between 43,000 and 89,000 approximately within the three groups of cohorts presented. In the case of parents, the control groups consistently present higher incomes and the treatment groups are mainly composed of fathers. In order to correct these aspects, the nearest neighbour method is used.

CUADRO 1

	Age group: 24-28		*Age group: 28-32*		*Age group: 30-34*	
	Control	Treat	Control	Treat	Control	Treat
Panel A: Sons/Daughters						
Male (%)	51.62	52.75	51.04	51.41	51.04	51.26
Income						
Mean	97,561	93,368	230,338	193,609	150,516	121,963
p25	16,249	16,055	42,754	35,272	21,032	16,321
p50	58,865	59,118	155,995	130,878	83,736	68,996
p75	138,709	135,660	332,570	287,764	204,371	166,655
N	78,512	10,476	51,545	5,602	39,299	3,697
Panel B: Parents						
Male (%)	33.80	59.25	22.00	44.24	12.33	26.62
Age (mean)	46.35	46.30	46.90	46.74	47.33	47.18
Income						
Mean	423,922	238,519	388,821	214,913	367,396	200,228
p25	165,907	76,992	154,265	68,888	148,127	60,448
p50	312,119	175,978	288,548	156,953	276,115	145,007
p75	542,349	331,850	499,467	302,159	477,982	281,807
N	53,042	7,543	34,696	4,051	25,465	2,457

Source: Own computations based on social security records.

[8] For this table the number of parents does not exactly coincide with the number of children, because we take into account fathers/mothers that have at least one child in the ages mentioned but could have more than one.

2.3 | Definition of earning variables

Permanent income We use a unique concept of earnings that exclusively covers wages and self-employed income. Labor earnings from different jobs are added up when workers hold multiple jobs within a year (or a month). As a result, a single vector of annual earnings is constructed for each individual, which aggregates all the wages for those workers who have multiple salary jobs in the same period. These earnings are before taxes and only incorporate taxable incomes, which excludes, for example, informal earning and non-contributory public transfers. Based on this definition of earnings, we use percentile rank-based measures of intergenerational mobility. We define percentiles by ranking the son of our sample relative to other individuals in their birth cohort that are included in the whole sample of administrative records. We proceed in analogous manners in the case of parents. Namely, we rank the sons and parents of our sample in the best measure of the formal earnings distribution. This strategy provides a more accurate measure of permanent income and position in society. Furthermore, attenuation bias is considerably weaker in intergenerational income/earning measures based on rank (Nybom and Stuhler, 2017; Mazumder, 2015).

Conventionally, to eliminate possible temporary fluctuations in earning levels both in the case of children and parents, we averaged 5 yearly rankings (or earning). This, in turn, reduces the possible measurement errors in the income of some years incorporated, reducing the effects of transitory fluctuations (Solon, 1989; Mitnik et al., 2015a; Chetty and Hendren, 2018).[9] Previous papers suggest that estimates of the IRA are comparatively more stable, less sensitive to the samples (and the presence of outliers in the tails), and to the specification choices (e.g. how earnings/income are defined and to the treatment of zero incomes in particular).(Dahl and DeLeire, 2008; Nybom and Stuhler, 2017; Chetty et al., 2014a; Mazumder, 2005)

Finally, intergenerational income/earning measures are sensitive to both life-cycle bias from heterogeneous age-income profiles (Nybom and Stuhler, 2017; Haider and Solon, 2006). Our samples consist of father-son pairs, with sons' earnings measured from age 28 to age 34 and parents' earnings measured from 45 to age 65.[10] Below we detail the criteria used in each case.

Children cohorts: We use two alternative criteria to define the children's permanent earning. First, we consider the children's labor earnings between the ages of 30 and 34. This allows us to construct a sample of children for 16 birth cohorts: from 1966 to 1981. Second, we consider the children's labor earnings between the ages of 28 and 32. With this criteria, we also identify 16 birth cohorts, in this case, from 1968 to 1983. Both groups of cohorts will be used to measure intergenerational earning mobility. We identify an additional group of younger cohorts in order to carry out additional analysis. We define alternative cohorts based on early-age of children to study the influence of fathers' displacement during the crisis of 2002.

The main decision for the elaboration of the permanent labor income - children's earning percentiles- is to determine the income distribution to be used for the construction of the percentiles. We use 2 alternatives:

A) Offspring percentiles rank based on average earning and the sample distribution: On this account, we define 5-years average based on the offspring annual earning. In this instance, we use the earnings distribution of the sample as reference, and we rank within each birth cohort and cross-section years all children samples. Then we define the 5-years

[9] Chetty et al. (2014a) argue that estimates from tax data tend to stabilize once 5 years of information are employed. But there is controversy about this point, Mazumder (2005) suggests that the results are sensitive to the number of years considered in the definition of life cycle earnings.

[10] Previous literature suggests that at age of 30 life-cycle income inequalities and intergenerational mobility measures begin to stabilize.

average -within our age of interest- based on the percentile ranks.

B) Average offspring percentiles rank based on the global distribution: In this case, we use the national distribution of formal earning within each birth cohort and cross-section year as reference. We define the child's percentile rank at age $\boldsymbol{i}$ based on his/her position in the complete distribution of formal earning relative to all other children in the same birth cohort. Note that, in this case, the child's percentiles correspond to his/her position in the worker population with the same age and birth cohort. Then we define the 5-years average based on the annual percentile ranks.

The latter is our preferred approach for defining the child's permanent earning. Given that we only have a sample of parent-child links, constructing a reference distribution only from this sample could give us an incorrect measure of the real position of these individuals in the global income distribution. This strategy allows us to avoid movements in the position of individuals that do not reflect changes in the percentiles of the whole earning distribution. Furthermore, this reference distribution is less influenced by the eventual sample's worker outflows from the labor market. The criteria A (offspring percentiles ranks based on average earning) is applied in our robustness checks. The use of both alternatives allows us to evaluate the validity of our sample of ties.

As we mentioned above, to study the influence of fathers' displacement during the crisis of 2002 we consider cohorts based on early-age of children. In this instance, we use the mentioned alternatives to define the rankings, but we consider the child's earning averaged across ages 24-28.

Parents' earning: We apply the following steps for the measurement of parents' permanent earning. i) We consider the earning that they received from ages 45 to 65.[11] ii) We identify the first year with a positive earning for this age range, and we consider the income received in the next 4 years (we seek to include information from the youngest). (iii) We define the parental earning as the largest earning of the parents (mother or father). (iv) For each selected age/year, we rank the parents of our sample in the global formal earning distribution from the universe of formal workers aged between 45 and 65. (v) We average the 5-years percentiles ranks for each parent (**Parents' percentiles based on global earning distribution**). As an alternative to steps (iv) and (v), we use the parent sample itself as a reference distribution to determine the percentiles. In this case, we construct the percentiles based on the 5-years annual earning (**Percentiles ranks based on average earning**).

In summary, for each individual i we construct a linked parent (p)-child (ch). We define an unique permanent earning for each child from the cohort c, Y_{ic}^{ch}, where c identifies the birth year ($c = 1966, 1967, 1968, ...$). The permanent earning of the parents, Y_{ic}^{p} is defined as the $max(Y_{ic}^{father}, Y_{ic}^{mother})$. In this case, we consider the first annual earning when parents have between 45-65. As a result, for each cohort c we built the joint empirical distribution of parent and child permanent earning $F_t(Y_{ic}^{ch}, Y_{ic}^{p})$, which will be used to measure intergenerational mobility and to explore the recent trend.

Second, we use two alternative definitions of earning. On one hand, the 5-years average includes years with zero income. This criterion establishes a lower bound from permanent earning. On the other hand, we use the same 5 years, but we excluded the zeros in the calculation of the average earnings of each generation. This criteria changes the permanent earning and defines an upper bound of the permanent income.[12].

[11] Nybom and Stuhler (2017) define fathers' income from age 33 to age 60. Due to data available we consider parents' earning at older ages, but as we explain below, within this age range we prioritize income earned at the youngest ages. This difference should not affect our estimates because earning stabilize around age 30. Chetty et al. (2014a) use an alternative criterion, considering parents income over the five years when the child is 15-19 years old.

[12] The first case is analogue to assume that when an individual declares zero annual income he/she is unemplo-

Third, for the elaboration of the permanent income, we use the national distribution of formal earning within each generation and cross-section year as a reference. Although this annual earning distribution only considers formal workers, the use of the total records instead of the sample allows us to incorporate workers with less stable links to the formal markets. This allows us to consider the instability of employment relations typical of the dual labor market from the developing economies. [13]

Intergenerational transmission of adverse shocks

Measuring the intergenerational effects of adverse events in the labor market involves analysing performance not only in permanent terms but also in current variables. In this case, we incorporate quarterly labor income as dependent variables as the first effect of the event of unemployment.

The estimation of the effect of negative events at the household level on the patterns of earnings of the second generation and the levels of intergenerational income mobility (questions 2 and 3) requires the definition of treatment and control groups. To define our treatment, we use the major macroeconomic crisis experienced by Uruguay around 2002, as a possible exogenous shock to households. As a first alternative, we identify the group of treated workers as those who enter the unemployment insurance between July 2002 and June 2003 (months in which the consequences of the crisis were concentrated, (Amarante et al., 2013)).

This definition of treatment implies considering the unemployment events of the sub-set of workers who meet the necessary conditions to obtain this benefit (at least three months of contributions in the year before the event). An alternative strategy is to include the group of workers who experience interruptions in the formal labor market, incorporating all the workers' separation regardless of whether they meet the conditions to receive unemployment insurance. This alternative incorporates a larger number of workers who experience adverse shocks, but it does not make it possible to distinguish movements to unemployment from possible transitions between the formal and informal labor markets.

As we will discuss in the empirical strategy, a potential concern for identifying the impact of the unemployment event is the degree of exogeneity of the shock. Exogeneity implies that unemployment events are not directly correlated with specific characteristics of the workers. To limit this possibility, we first exploited the unemployment events that occurred around the 2002 crisis, exploiting the increase in layoffs caused by the adverse macroeconomic shock experienced by the firms. Figure 2 shows the strong increase in the number of individuals sent to unemployment insurance around 2002. Given the characteristics of the shock and the magnitude of the increase in layoffs, the probability of voluntary or discretionary separations is reduced.

However, even in this context, firms could select laid-off workers according to their characteristics. In future steps of this research, we explore a third alternative to define the treatment group, exploiting the set of firms that experience mass layoffs or plant closures

yed or inactive. The Based on these definitions of earnings, we use percentile rank as our preferred permanent income measure (R_{ic}). The recent literature highlights the advantages of ranking variables to measure intergenerational mobility over alternative measures in terms of lower attenuation and life cycle biases, and the treatment of individuals without income (Nybom and Stuhler, 2017; Chetty et al., 2014a; Mitnik et al., 2015b)

Given the presence of a relevant informal sector in the economy, in this research, we decided to use different alternative strategies. First, our baseline measure of intergenerational earning considers sons aged 30 to 34 (or 28 to 30) years and parents from 45 to 65. In this range, the incidence of informal work is substantively lower. Second case is analogue to assume that when an individual declares zero annual income, he/she obtains the average income of the other years in the formal sector but in the informal sector

[13] Leites et al. (2021) used a similar strategy but also consider as reference the global income distribution adding the informal sector earning, which was fitted from the National Household survey. Their estimates of IRA based on both alternatives show a similar level.

during the crisis. This reduces the possibility that the dismissals are linked to characteristics of the workers, mitigating the problems of selection bias associated with the worker characteristics.

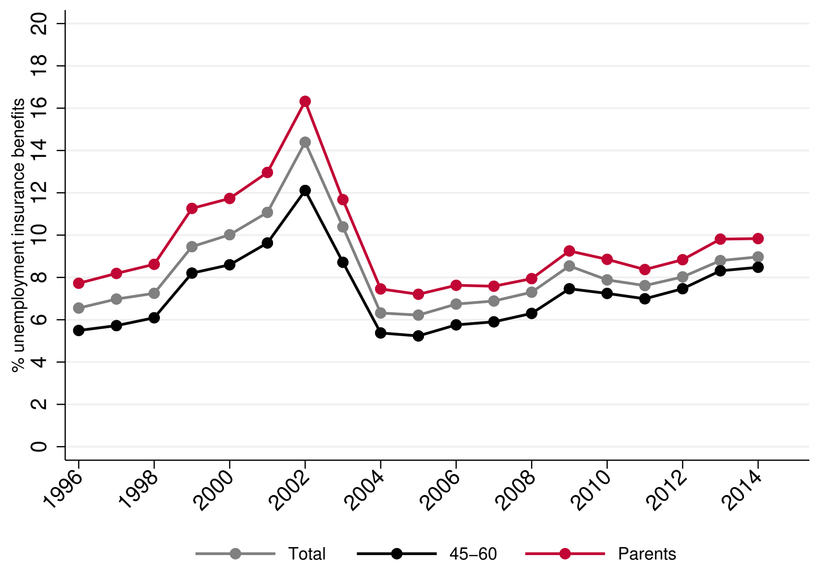


FIGURA 2 Proportion of workers on unemployment insurance per year. *Notes:* The grey curve represents the total of formal workers; the black curve restricts the age between 45 and 60 years; while the red one considers only the workers who are identified as parents. *Source:* Own elaboration based on social security records.

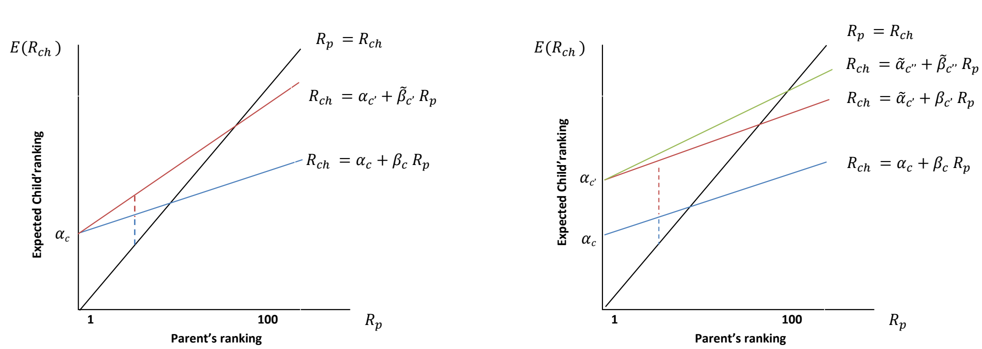
2.4 | Mobility measures and econometric models

In this section, we describe the empirical strategy used in this paper to address the three research questions. First, we present the strategy that we use to measure intergenerational mobility and answer the first research question. Second, we describe the strategy used to identify the mechanisms underlying intergenerational mobility and to respond to the second and third research questions. In this case, we describe in detail the identification strategy, which exploits the effect of the macroeconomic shock on parental unemployment.

2.4.1 | Measuring intergenerational earning mobility

We present the summary measures that will be used to approx intergenerational mobility for each cohort. It is usual in the intergenerational mobility literature to use a single parameter as a measure of intergenerational mobility. Naturally, using a single parameter at the cohort level facilitates comparisons between cohorts and assessing the trend. However, like any summary measure, it provides an incomplete description of mobility, so it is relevant to specify what we are measuring.

Our measure of permanent income is based on the earnings rank of each cohort and generation. Graphs a and b in Figure 3 describe the summary measures by cohort that will be used in this paper. To start, consider a linear intergenerational relationship between child's earning rank (R^{ch}_{ic}) born at cohort c and parent's earning rank (R^{p}_{ic}). Graphically, this relationship for cohort c is described by the blue line, which represents the conditional expectation of the child's earning rank given his parent's rank. This relationship is described just by two parameters: a slope (β_c) and an intercept (α_c). The slope of the blue line identifies the correlation between children's and parents' rank in the earning distribution. It is a common summary measure of intergenerational persistence and it provides an average measure of the strength of the association in the copula of the joint distribution (Mitnik et al., 2015a). This parameter is a measure of relative mobility because it captures the difference in the ranking between children from top vs bottom earning parents within the cohort c. While the intercept (α_c) represents the expected rank for children from parents at the bottom of the earning distribution. The intercept provides a measure of absolute mobility for this group of children (the vertical distance represents the difference between the expected rank of these children and the rank of their parents). [14]



(a) Same intercept by cohorts

(b) Different intercepts by cohorts

FIGURA 3 Measuring relative and absolute mobility by cohorts. *Notes:* The y-axis represents the the expected child's earning rank R^{ch}_{ic} and x-axis represents the parent's earning rank (R^{p}_{ic}). *Source:* Own elaboration adapted from Hertz (2009).

Graph (a) in the Figure 3 shows that the cohort c (blue line) has a greater relative mobility than cohort c' (red line). Both cohorts have the same intercept (α_c), so the slope reflects the relative mobility when the children from parents at the bottom of the earning distribution start from the same situation (the same expected rank). In this case, the measure of relative mobility is based on a situation where the expected result of the children from the bottom of the distribution is fully comparable. Graph (b) in Figure 3 describes a situation where the cohorts c'' (green line) show changes in terms of absolute and relative mobility. The cohorts c' and c'' (red and green lines respectively) show greater absolute mobility than the cohort c, while, the cohorts c and c' have the same relative mobility, but they are greater than c''. However, the comparability β as relative mobility measures is conditioned by the fact that the these curves have different starting points.

To answer question P1, we use a reduced form modelling approach to estimate (β_c) and assess the intergenerational permanent earnings association between children from the cohort c and their parents/mothers. We regress the child's earning rank from the cohort c and household i, R^{ch}_{ic} on the parent's earning rank (R^{p}_{i}). As a benchmark, we first measure the average intergenerational mobility and consider jointly all cohorts that we identify in our samples. In this case, we estimate a $\beta^{average}$ which characterises mobility based on

[14]Note that the vertical distance between the expected rank of the children and the 45-degree line represents a measure of the expected mobility. It is the difference between the conditional expectation of the child's rank and the rank of their parents (vertical dotted line). Note that this distance is greater when (α) and (β) are higher.

a unique rank-rank relationship for the period. The specification presented in equation 1 allows us to estimate $\beta^{average}$, which represents the average relative mobility for all cohorts.

$$R_{ic}^{ch} = \alpha + \beta^{average} R_i^p + \lambda X_{ic} + \nu_{ic} \tag{1}$$

where the superindex ch and p identifies the child and parents, X_i represents a set of standard control variables used in the intergenerational income literature: child's sex, parental'sex and parental age. Each child i belongs to one cohort c, where $c = 1966, 1967, 1968....$ As a result, equation (1) considers child's and parent's permanent income and its estimation is based on cross-section data.

Second, in order to explore trends in intergenerational mobility, we estimate our intergenerational mobility measure by birth cohort. In this case, we use the equation (2) to estimate one β_s for each cohort (or group of cohorts) which follows Davis and Mazumder (2020).

$$R_{ic}^{h} = \alpha + \sum_{0<s<m} \beta_s' T_s * R_i^p + \lambda X_{ic} + \nu_{ic} \tag{2}$$

where T_s' is a function that identifies a set of cohorts that we consider as one same group. When s=1 we estimate one β_s' for each cohort. As Table A.1 in the appendix shows, when the child's earnings are averaged over the age range 30-34 the sample size of the oldest cohort is relatively small. For this reason, the composition of the cohorts of our sample, we estimate the parameters of interest with Weighted Least Squares instead of Ordinary Least Squares. We weight each individual by the inverse of the number of individuals in the same cohort.[15] Testing the statistical significance of the difference between β_{s_1}' and β_{s_2}' we explore the changes in the long-term relative intergenerational earning mobility. Note that this strategy allows us to assess the change in relative mobility between cohorts described in Graph (a) in Figure 3. Testing the statistical significance of the difference between β_s and $\beta^{average}$ we explore whether some cohorts present higher (or lower) relative mobility than the average.

In order to consider potential changes between cohorts both in terms of relative and absolute mobility, we incorporate the specification used in Chetty et al. (2014b), which incorporate one intercept by cohort.

$$R_{ic}^{h} = \sum_{0<s<m} T_s * \alpha_s'' + \sum_{0<s<m} \beta_s'' T_s * R_i^p + \lambda X_{ic} + \nu_{ic} \tag{3}$$

Testing the statistical significance of the difference of β_s and α_s between cohorts, we explore the changes in these measures of relative and absolute mobility. Note that α_s represent a fixed effect for cohort, which captures all shared characteristics within a generation (common shocks, offspring's earning distribution and parent's earning distribution). Beyond the conceptual interpretation of these parameters which, as mentioned, measure different aspects of mobility, by construction their estimation has a mechanical relationship. For this reason, it is expected that the β_s estimates based on equations 2 and 3 will present variations.

[15] Also, in some cases, we include estimates based on three age-grouped cohorts (s=3) in order to increase the number of observations.

One important point to interpret appropriately the potential changes in intergenerational earning mobility is the fact that earning inequality may have changed during the period of analysis. This issue has significant implications to estimate the intergenerational income elasticity for long-term period. However, the consequences would be minor for the measurement of the IRA given the normalization of the earning distributions for each generation. In the context of this study, this applies to the case of percentiles ranks based on the 5-average earning distribution within the sample and generation. However, the distribution of percentiles of our sample may change when the children and parents percentiles are based on the real position of these individuals in the global earning distribution of their generation. Again, this is not a problem to the children's percentiles, because our sample is representative of their cohort and the ranking based on sample or global distribution is very similar. However, the profiles of the parents and their position in the global earning distribution may vary along the period.

To address this issue we estimate the Spearman rank correlation for each cohorts:

$$\rho^c = \frac{Cov(R^h_{ic}, R^p_i)}{\sqrt{Var(R^h_{ic})Var(R^p_i)}} \tag{4}$$

There is a direct relationship between ρ^c and β''_s defined by

$$\rho^c = \beta''_s * \frac{SD(R^p_i)}{SD(R^h_{ic})} \tag{5}$$

where $SD(R^p_i)$ and $SD(R^h_{ic})$ represent the standard deviation for the parents' and children's' percentiles. For example, if the variance of parents' earning increases over time, it would lead to downward the magnitude of β. This could be corrected by using ρ^c, in which β is adjusted for potential changes in inequality.

The equations 2 and 3 model a linear relationship between parents and children's permanent earning. The assumption of linearity assures that (β) is both locally and globally informative and β' is interpreted as the average difference in the mean percentile/position rank of children from the richest families vs. children from the poorest families.

This generic form allows us to model linear or nonlinear relationship between R^p_{ic} and R^h_{ic}. When $f(\cdot)$ is the identity function, we assume a linear relationship between permanent earnings of both generations.

A more flexible specification allows us to relax the linearity assumption and evaluate whether the degree of intergenerational mobility is constant throughout the income distribution of the parents' generation. We use an alternative strategy based on a generic form, which allows us to model linear or nonlinear relationship between R^p_{ic} and R^h_{ic}. In turn, it allows us to assess whether this functional form changed across cohorts. For this purpose, a more flexible version of the previous equations will be used, exploring the presence of nonlinearities, in particular, at the upper tail of the parental earning distribution. To explore the presence of nonlinearities we carried out non-parametric methods suggested in Mitnik et al. (2015b), which relies on local polynomial regressions (Cleveland et al., 1988). The model is defined as:

$$E(R^{ch}_{ich}|R^p_{ic}) = G(R^p_{ic}) \tag{6}$$

where G is a smoothing function. This expression represents the expected rank of the offspring conditional on parental rank. Although this model offers a more flexible way and avoids the discussion of the inclusion of the intercept, it has the disadvantage that it does not provide a summary indicator that synthesizes the mobility levels of a cohort.

2.4.2 | Intergenerational persistence and directional mobility

In order to provide complementary perspectives on the degree and nature of mobility in the long term, we use some alternative measures of income mobility.

First, following Corak et al. (2014) we estimate the upward transition probability (UTP) for each cohort c (or groups of cohorts s) as the probability that the child's percentile exceeds by an amount τ a given ranking position m, in the earnings distribution of its generation, conditional on the parent's income ranking being lower than m.

$$UTP_c^{\tau,m} = Pr(R_{ic}^{ch} > m + \tau | R_i^p \leqslant m) \tag{7}$$

In our empirical analysis, we use $UTP_c^{40,50}$, which represents the probability that a child is at the top decile of the children's generation conditional on parents' earnings being in the bottom half of the distribution of the parent's generation.

Alternatively, we use upward directional rank mobility for each cohort c (or group of cohorts s), UP_c (or UP_s). In this case, following Corak et al. (2014) we estimate the probability that for a given child i from cohort c (or s), the child's ranking in its generation exceeds the parent's earning ranking by an amount τ, conditional on its parent's income percentile is below m.

$$UP_c^{\tau,m} = Pr(R_{ic}^{ch} - R_i^p > \tau | R_i^p \leqslant m) \tag{8}$$

When $\tau = 0$, the $UP_c^{0,m}$ represents the probability that the child's ranking exceeds the parent ranking (each one in the distribution of their own generation). Following Corak et al. (2014) we classify these children as upwardly mobile (UM). In our empirical analysis, we also consider $\tau = 5$ which allows us to consider the amount of the gain in positions across generations (UM_5).

Finally, we consider the persistent transition probability, to measure the relevance of the diagonal cells and a set of neighboring cells.

$$P_c^{\tau} = Pr(-\tau - 1 < R_{ic}^{ch} - R_i^p < 1 + \tau | R_i^p) \tag{9}$$

When $\tau = 0$, P_c^0 is the proportion of children that (in their generation) persist in the same position as their parents. We also use $\tau = 5$ to measure the persistence within a small range of percentiles.

2.4.3 | The effect of the 2002 crisis on level of intergenerational earnings mobility

This section describes the empirical strategy used to analyze the potential effects of the 2002 crisis on the labor trajectories of the children's generation (research questions 2 and 3). To do so, we first present a model that allows us to identify whether the crisis had an effect on the income of the first generation (section 4.1). This first step has only instrumental objectives and allows us to discuss the identifying assumptions for the causal interpretation of our coefficients of interest. Then, we will focus on the models to estimate the intergenerational transmission of current and permanent earnings (section 4.2).

The effect on the parents' generation

Adverse events associated with an economic crisis can generate significant and long-lasting impacts on the income trajectories of the workers who experience them. However, our main interest is to evaluate whether part of these potential negative effects is transmitted between generations. To determine the effect of this channel between generations, we first analyze the existence and magnitude of the direct effect of the unemployment shock.

We estimate a panel event-study to estimate the effect on the parent's generation (see equation 10). We define a variable $Event_i$ as the moment of time in which the workers experienced the unemployment event. Our treatment includes as an event the set of workers who experienced a separation from the labor market around the 2002 crisis (between July 2002-June 2003). Our main specification for this stage includes potential lags and leads effect of the shock on our main variable of interest, the parent's labor incomes (Y^p_{it})[16]:

$$Y^p_{it} = \alpha + \sum_{j=2}^{J} \delta_j (Lag)_{it} + \sum_{k=1}^{K} \delta_k (Lead)_{it} + \gamma_t + \mu_i + \lambda X_{it} + \nu_{it} \tag{10}$$

The panel event-study specification allows us to include time (γ_t) and individual fixed effects (μ_i), and sociodemographic characteristics of parents as control variables (X_{it}). In turn, it allows estimating heterogeneous effects of the event over time. Our variables of interest are the dummies who identified the lags and leads of the event:

$$(Lagj)_{it} = 1[t = Event_i - j], j \in (1, ..., J-1)$$

$$(Leadk)_{it} = 1[t = Event_i + k], k \in (1, ..., K-1)$$

We include dummies who accumulate the effect beyond J and K periods:

$$(LagJ)_{it} = 1[t \leqslant Event_i - J]$$

$$(LagK)_{it} = 1[t \geqslant Event_i + K]$$

In this sense, the event variables are normalized to the moment of the shock experienced for the treatment group. The workers without separations shocks (without events) act as the control group, as in a difference-in-difference approach. As standard in event study literature, we omitted the first lag in the equation 10. Hence, lags and leads capture the difference between treated and control workers, compared to the difference in the omitted base period $t = -1$.

As in the difference-in-difference models, the identification strategy is based on the assumption of parallel trends before the event (Clarke and Schythe, 2020). In our case,

[16] Next we use the notation of Clarke and Schythe (2020). Similar models are applied, for example, by Freyaldenhoven et al. (2019); Callaway and Sant'Anna (2021)

the assumption implies that workers who did not register unemployment events during the 2002 crisis represent a good counterfactual for our treatment group. In this sense, the set coefficients of the periods before the event ($Lead_k$ coefficients) allow us to test this assumption.

The identification assumption of this model assumes that the separation of the employment relationship is exogenous for the worker, and is not a voluntary exit from the labor market. Focusing on layoffs in a macroeconomic shock, such as the 2002 crisis, diminishes the probability of voluntary separation, but does not exclude the possibility that separations from the labor market may not be random and respond to characteristics of workers. Firms can dismiss workers based on observable and unobservable characteristics as qualifications, skills, or wage levels. The individual fixed effects allow us to control part of this potential selection of the treated workers, but the effects of characteristics that change over time and explain the selection of workers to be dismissed may persist.

Intergenerational effects on the second generation

The previous empirical strategy focuses on identifying the direct effects on the labor trajectories of first-generation individuals after an adverse shock. However, the negative effects of this event may produce additional consequences on the entry and progression in the labor market of their children through different mechanisms: household financial restrictions, losses in specific human capital, destruction of social capital and networks. The intergenerational effects of the adverse shock experienced by parents will be assessed from two perspectives. The first one emphasizes short-term performance, observing the impact on the current income of children at the beginning of their labor market career. The second one focuses on the long-term performance of the children in terms of their permanent income and its link with the permanent income of their parents.

To evaluate the incidence of the job separation that parents experienced in 2002 on the performance of their children, we will adopt a specification similar to Oreopoulos et al. (2008):

$$Y_{it}^{h} = \alpha_i^{h} + \gamma_t + \sum_{k \geqslant m} D_{it}^{k}\delta_k^{h} + \lambda X_{it} + \nu_{it} \tag{11}$$

The variable D_{it}^{k} identifies the unemployment event in the parents' generation. Y_{it}^{h} represents the current earnings of the children. The δ_k^{h} parameters identify the effect of parental job separation on children's labor market performance. Again, the identification of the effect depends on the exogeneity of the shock experienced by the parents. The validity of the causal interpretation of the estimates also requires similar trends between control and treatment groups.

Finally, we will analyse the potential effects of the shock experienced by the household on permanent income and the degree of intergenerational persistence. In this link, it is particularly relevant to distinguish between monetary factors and the possible innate transmission of characteristics and skills. In this context, if the exogenous shock affects the parents' work path and their permanent income, and its incidence is independent of the characteristics that are transmitted innately, the incidence of the shock can be used to distinguish the empirical relevance of the economic mechanism. In this case, we use an adaptation of the Bratberg et al. (2008) model.

$$R^h_{ic} = \alpha_c + \theta_d D^{02}_i + \beta R^p_{ic} + \theta_c R^p_{ic} D^{02}_i + \lambda_1 X_{ic} + \nu''_{ic} \tag{12}$$

This model includes an approximation of the permanent income of the children R^h_{ic} as the dependent variable and incorporates the permanent income of the parents R^p_{ic} as an explanatory variable. Unlike the previous equations, it is not possible to incorporate fixed effects since we do not have temporal variability in the permanent incomes of both generations. The characteristics of the parents are included in permanent income and the sociodemographic controls.

This specification makes it possible to analyse two channels of intergenerational transmission. The parameter β identifies the average transmission and therefore is a proxy for an IRA estimate for this sub-sample. Second, the parameter θ_c identifies the effect of the unfavourable event in the household on the permanent income of the second generation. In both cases, these effects are mediated by the parents' generation. On the other hand, the parameter θ_d summarises the direct effects that children could have experienced due to the unemployment shock at the household level.

The estimation of the effects on the generation of children creates a trade-off between the measurement of permanent income at central ages of the life cycle and the possibility of measuring effects experienced by children at different ages. Therefore, we build permanent incomes definitions at younger ages, to be able to incorporate children who suffered the shock before their 20 years. If there are no significant differences in the bias generated by the life cycle between the control and treatment groups, the estimated effect should not be biased by the use of younger ages (Bratberg et al., 2008).

3 | LONG-TERM EARNINGS MOBILITY

Following prior research, we use many statistics to measure intergenerational earning mobility trends: (i) Intergenerational Ranking Association (IRA); (ii) ranking correlation coefficients (iii) children's earnings expectations conditional on parental income; and (iv) intergenerational persistence and directional mobility. Since each of these measures could exhibit different time trends, we report the estimates for each cohort. The results regarding (i) and (ii) are presented in subsection 3.1, while the results regarding measures (iii) and (iv) are presented in subsection 3.2.

3.1 | Long-term earnings mobility: Intergenerational Ranking Association

To start with, we estimate an Intergenerational Ranking Association (IRA) measure for our baseline samples of children cohorts presented in subsection 2.2. Figure 4 presents our primary estimates of IRA by birth cohort. It focuses on relative mobility and presents the rank-rank slopes for the 1966-1981 birth cohorts, using the children at ages 30-34. These estimations are based on equation (2), using a rank-rank specification and assuming a constant slope for each birth cohort and a unique intercept for all cohorts. Furthermore, we include the average IRA estimates based on equation (1). To duly take into account the composition of our cohort samples, our estimates are based on Weighted Least Squares (WLS). We control for the age and sex of the parents and the sex of offspring in all regressions.

Panel (a) and (b) in Figure 4 present the IRA using two alternative concepts of permanent income. While the first one is based on a 5-years average including zeros (which establishes a lower bound for permanent earnings), the second one excludes years with zero earnings (and establishes an upper bound for permanent earnings). The solid points are the point estimates for each cohort, while dashed grey lines are the confidence intervals, and the continuous line is the weighted average IRA for the groups of cohorts. Those birth cohorts whose coefficients are not significantly different from the average are marked with a red point, otherwise they are marked with a blue point. Observe that changes in the coefficients could be directly interpreted as changes in the intergenerational earning persistence (Hertz, 2009).

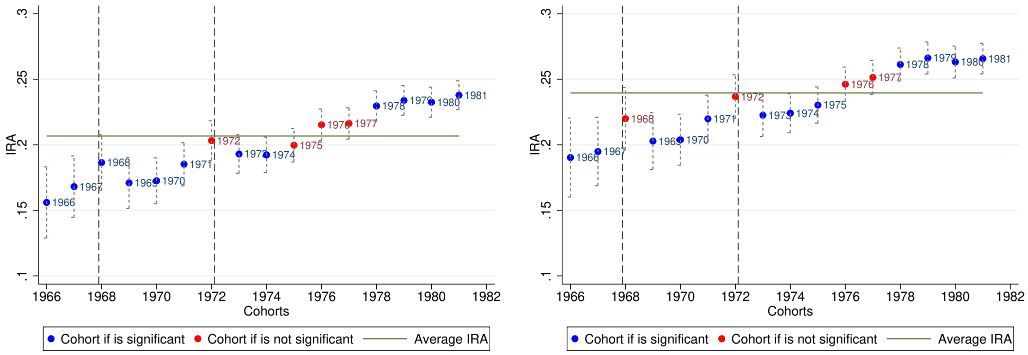
The average IRA estimates for children at ages 30-34 and the two concepts of permanent earning is between 0.21 and 0.24. However, Figure 4 demonstrates that this average conceals substantial heterogeneity across birth cohorts. In Panel (a) the coefficients of birth cohorts between 1966 and 1975 are statistically significantly lower than the average IRA. Panel (b) shows similar results.

For both definitions of permanent income, statistical tests reject the hypothesis that the IRA coefficients of cohorts 1972, 1976 and 1977 are different from the average coefficient. This result is likely related to... On the other hand, mobility seems to be lower for the latest cohorts, which shows an IRA above the average. For the 1978-1981 birth cohorts the null hypothesis of equality of cohort's IRA to average IRA is rejected at 5 % confidence. Furthermore, the IRAs for the 1978-1981 cohorts are significantly higher than the IRA for the 1966-1971 cohorts.

Beyond the above-mentioned heterogeneity, the rank-rank-based measure of mobility suggests an increasing tendency from earlier birth cohorts to the more recent cohorts. For instance, the first 10 cohorts present IRA coefficients below the average , while the latter cohorts are above the average. These results suggest that rank-based measures of mobility remained relatively stable and below the average for the cohorts between 1966-1975, but intergenerational earnings persistence increased over the cohorts 1978-1981.

In sum, the results based on Figure 4 and equation (1) suggest a significant decline in the degree of intergenerational earning mobility across cohorts. Within this long-term picture, it is relevant to explore the role of the 2002 crisis, particularly, we inquire whether is related to the observed tendency.

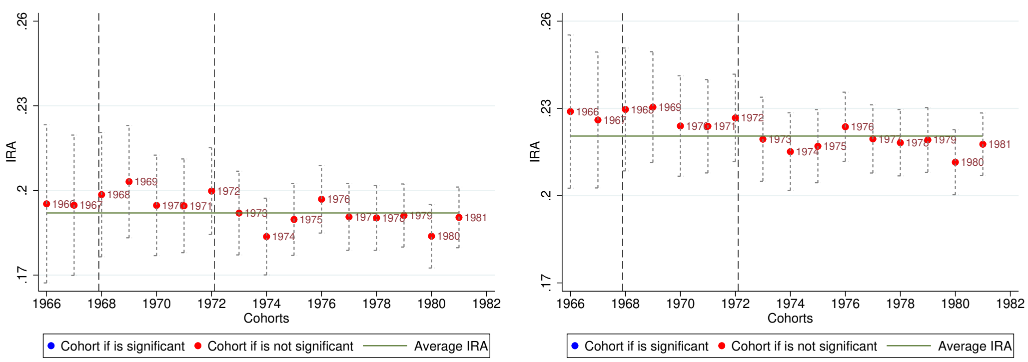
To advance in this analysis of intergenerational mobility of our group of cohorts, we modify the reference distribution used for the construction of the ranks. Figure 5 presents estimates analogous to those shown in Figure 4, but when we use the percentiles ranks based on the 5-years earning average and the sample distribution of parents and children separately. Panels (a) and (b) summarise the results for the two alternative definitions of permanent earnings. The average levels of intergenerational mobility found are similar to those reported in the previous estimates, although a bit lower. Both panels show a very similar pattern for the two notions of permanent income, although the differences between birth cohorts are less pronounced than the results presented in Figure 4, and the significance of the differences between cohorts (and between them and the average) is null.



(a) Permanent income includes zero

(b) Permanent income excludes zeros

FIGURA 4 Intergenerational Ranking Association by cohort. Global earnings distribution (cohorts when child is aged 30 to 34). *Notes:* The dependent variable is the average offspring percentiles rank. Children and Parent percentiles based on global earning distribution for each generation. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. Panel (a) 5-years average includes years with zero earning. Panel (b) 5-years average only includes years with positive earning. Coefficients are WLS estimates, over 100,850 observations. Controls: children's sex, parent's age, and parent's sex. *Source:* Own elaboration based on social security records.



(a) Permanent income includes zeros

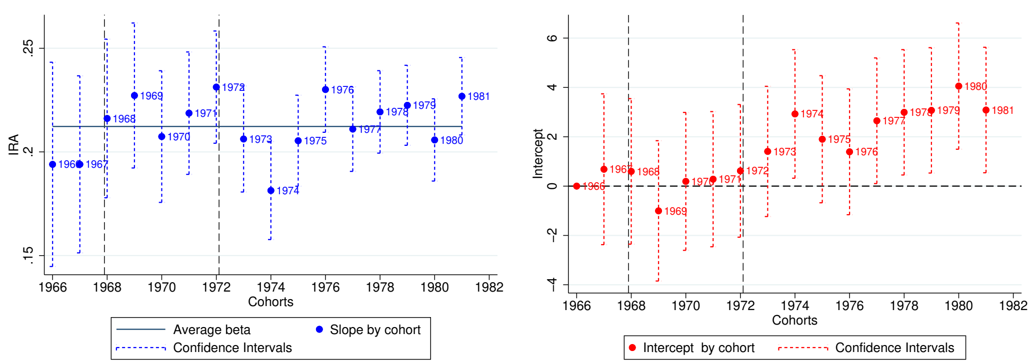
(b) Permanent income excludes zeros

FIGURA 5 Intergenerational Ranking Association by cohorts. Own sample earning distribution (cohorts when child is aged 30 to 34). *Notes:* The dependent variable is offspring's percentiles rank based on average earning. Children and Parent percentiles based on own sample earning distribution for each generation. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. Panel (a) 5-years average includes years with zero earning. Panel (b) 5-years average only includes years with positive earning. Coefficients are WLS estimates, over 100,850 observations. Controls: children's sex, parent's age, and parent's sex. *Source:* Own elaboration based on social security records.

The previous results are based on equation 2, which assumes a unique intercept. This specification allows better comparability between cohorts to evaluate differences in terms of IRA coefficients. In this case, the changes in the coefficients could be interpreted as changes in the intergenerational earning relative persistence. To advance in this analysis, Figure 6 present estimations based on equation (3), which uses a rank-rank specification and assume one slope and intercept for each birth cohort. The rankings are based on global earning distribution of each generation. Panels (a) and (b) respectively show the estimated slopes and intercepts for each cohort. Two main results emerge from this model. First, unlike the previous results based on equation 2, the slopes remain stable for each cohort and they are not significantly different from the average IRA. Slopes from almost all cohorts remain close to a mean of 0.21, very similar to those average IRA estimated for the global earnings distribution with only one intercept (see Figure 4). Second, the result regarding the intercept suggest a small increase of the intercept for the latest cohorts, but with no significant differences among them.

The estimates that emerge from equations 2 and 3 provide ambiguous results regarding relative mobility. In other words, the evolution of the IRA between generations is very sensitive to the treatment of the intercept. While the first of this specification facilitates comparability of IRA between cohorts, the second specification allows controlling for specific children cohorts' effect. As we discussed 2.4, changes in the earning inequality during the period of analysis may affect the level of our measure of intergenerational earning mobility. In particular, when ranking are based on global income distribution the intergenerational inequality of the parents' generation could change for the different cohorts of children, which mechanically alters the level of the estimated IRA. As Table A.4 shows, while the intragenerational inequality for children remains relatively stable (measured through standard deviation in column 4), the earning inequality for the parents has increased throughout the generations (Column 7). In fact, the ratio of the standard deviations (Column 8) increases from 0.62 to 0.88. This change has implications both to establish the level of IRA as to interpret what represents the magnitude obtained in our estimates. The Spearman rank correlation defined in 3.1 has a direct relationship with the IRA estimated based on equation 3, but allows adjusting the IRA coefficient for potential changes in inequality (see equation 5 in section 2.4).

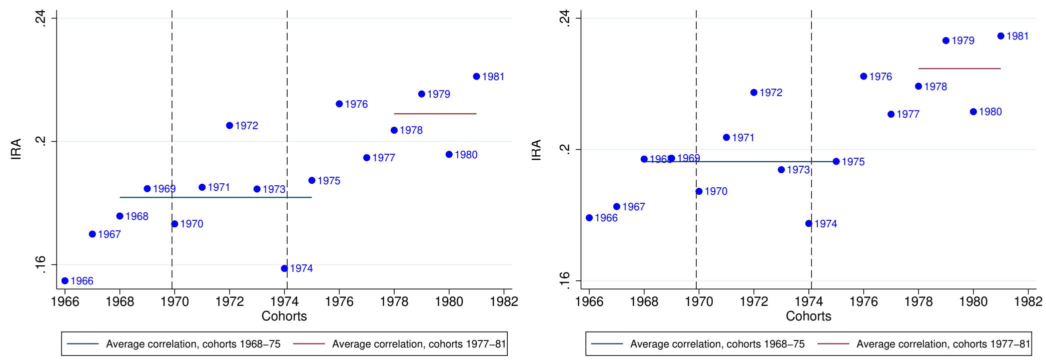
To address this concerns, Figure 7 presents the estimates of the Spearman rank correlation for each cohorts. Although heterogeneity between cohorts remains, the trend is much noisier and suggests a decline in mobility. When we consider the average for the 1978-1981 birth cohorts, the coefficient of correlation is 0.21 (Panel a), while for the 1970-1974 cohorts is 0.18. When the permanent income excludes zeros (Panel b), the averages are 0.22 and 0.20 respectively.



(a) Slopes

(b) Intercepts

FIGURA 6 Intergenerational Ranking Association by cohorts, multiple intercepts. Global earning distribution (cohorts when child is aged 30 to 34). *Notes:* The dependent variable is the average offspring percentiles rank. Children and Parent percentiles based on global sample earning distribution for each generation, 5-years average includes years with zero earning. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. Coefficients are WLS estimates, over 100,850 observations. Controls: children's sex, parent's age, and parent's sex. *Source:* Own elaboration based on social security records.



(a) Permanent income includes zero

(b) Permanent income excludes zeros

FIGURA 7 Spearman rank correlation by cohort. Global earnings distribution (cohorts when child is aged 30 to 34). *Notes:* The dependent variable is the average offspring percentiles rank. Children and Parent percentiles based on global earning distribution for each generation. Panel (a) 5-years average includes years with zero earning. Panel (b) 5-years average only includes years with positive earning. Coefficients are Spearman estimations, over 100,850 observations. *Source:* Own elaboration based on social security records.

The previous results aim to answer the research question 1. In sum, the joint reading of the results of the equations 2, 3 and 3.1 suggest that the relative mobility did not increase for the analysed cohorts. We found evidence of a very slight drop in mobility, although the evidence is noisy. Regarding absolute mobility, the results are ambiguous but suggest a slight increase for the cohorts 1979-1981 (either due to an increase in the slope or the intercept).

Intergenerational mobility and gender

We also explore the tendency on intergenerational mobility by children's sex for extended and universal samples. Children's gender has been found to be a source of heterogeneity in the intergenerational transmission of economic advantage. This point is particularly relevant considering the increasing tendency of labor female labor force participation rate in Uruguay (Espino et al., 2017). For less-education unskilled workers, there was a gender gap in the formality of employment in some sectors (e.g. domestic workers), which has been reduced significantly (Carrasco et al., 2018) [17]. We replicate the estimations presented in Figures 4 but fit the model for sons and daughters separately. The results of those estimates are presented in Figure B.1 and for both groups, it shows a similar pattern. Although there is a difference in level and the estimated IRA is a bit higher for son than for a daughter, the same tendency as previous results is confirmed in both cases. [18]

Intergenerational mobility and business cycle

The previous results have to be interpreted with caution, because our IRA estimates are very sensitive to the specification used. A particular concern when interpreting the results on the evolution of intergenerational mobility is to consider how our estimates could be affected by the effects of the 2002 crisis. First, our measure of permanent earnings could be affected by the business cycle. If so, this could partly explain the heterogeneity found in the

[17] A specific concern is related to the recent trend in the labor market, which shows an increase in the participation of formal workers. This could reduce comparability between the extreme cohorts of our sample.

[18] We replicate these estimates by children's gender, but when children are 28-32 years old, which includes the 1968-1983 birth cohorts. The results are the same, and they are available upon request.

IRA coefficients across cohorts. As a first robustness check, the estimates presented above use two alternative definition of permanent earnings, which represents the lower and upper bound of the permanent income respectively (see Section 2.3)

As a second robustness check, we also replicate the estimations in Figures 4 and 5 but considering the birth cohorts when children are younger, which allows the economic cycle to affect them at a different time of the life-cycle. Figures B.4, B.2 and B.3 in the Appendix show the rank-rank slopes for the 1968-1983 birth cohorts when children are 28-32 years old. The size of the average IRA estimates are similar, although, as expected, they are a bit lower than the estimates discussed in previous paragraphs. The evidence on trends in intergenerational mobility is similar to those reported in the previous Figures for the birth cohorts 1966-1981, although, in this case, the differences in intergenerational income mobility across cohorts are significantly lower. We replicate this exercise by changing the age of the cohorts (and the timing of the business cycle and its effect on the permanent earning) to 24-28 (Figure B.5 in the appendix).

Figure 8 summarises this analysis, and allows us to describe the role of the 2002 crisis on the IRA for the three alternative definition of cohorts. The comparison for each cohort of the three measurements shows the sensitivity of the results to the age group used. Due to being in an early stage of the labor career, the estimates for the 24 to 28 age group are systematically lower, showing the usual life-cycle bias. However, the differences between the remaining age groups are minor, suggesting that the use of the 24-28 group does not imply the incorporation of relevant biases in the estimations. Secondly, the measurements using the 24-28, 28-32 and 30-34 ages exhibit an increasing trend, suggesting a decline in relative mobility for those cohorts between 1976-1983. These results seem to be consistent with the previous results regarding the research question 1.

Finally, the measurements that incorporate income in years next to the macroeconomic crisis of 2002 show systematically lower levels of persistence in all cases. For example, the cohort 1978, which presents a relatively low IRA when children's permanent earning is measured at 24-28 (it includes earnings from 2002 to 2006). These estimates are represented by the lowest blue point in the series. However, the IRA coefficient for the same cohort but measured when children had 28-32 or 30-34 -and the permanent income does not included the 2002 yearly income- is relatively high in the series (see red and green points). In the case of estimates using ages between 30 and 34 years (green points), the cohorts around 1972 that incorporate income from 2002 or later show the lowest IRA levels.

In sum, when we use a more flexible version of offspring permanent earning and we estimate alternative IRA coefficients for the same cohort but considering separately alternatively age ranges, the results suggest that the measurement is sensitive to how the effects of the 2002 crisis are incorporated into the offspring's permanent income. The IRA coefficients tend to be lower for those cohorts in which children's permanent earnings incorporate the potential direct negative shock of the macroeconomic crisis of 2002. In those years, the affected cohorts show higher levels of relative mobility.

It is important to point out that our mobility measurements are considering ages where the children's income is expected to be relative stable, given the moment of their life cycle. However, these results suggest that measurements of intergenerational mobility could be sensitive to the shocks' effects. Finally, observe that this result describes how the shock of 2002 affects the measurement of intergenerational mobility through offspring earnings, but it does not consider how the shock affects the older generation. In this sense, it does not describe whether the crisis altered intergenerational transmission, nor explore the transmission mechanisms of the adverse shock. We will advance in this issue in the section 4, when we address the effects of unemployment events experimented by the parents around the 2002 macroeconomic crisis and its consequences to the next generation.

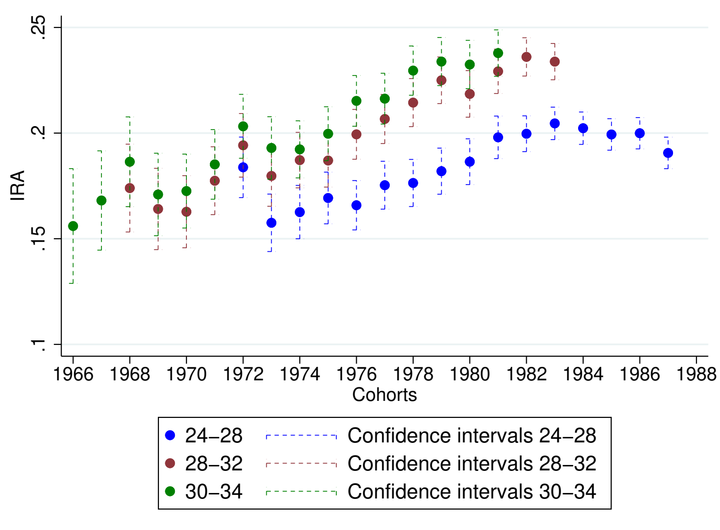


FIGURA 8 Intergenerational Ranking Association by cohorts. Global earning distribution (cohorts when child is aged 24-28, 28-32 and 30-34). 5 years average includes zeros. *Notes:* The dependent variable is the average offspring percentiles rank . Children and Parent percentiles based on global sample earning distribution for each generation. 5-years average includes years with zero earning. Coefficients are WLS estimates, over 100,850 observations (for cohorts 30-34), 131,895 observations (for cohorts 28-32) and 204,121 observations (for cohorts 24-28) . Controls: children's sex, parent's age, and parent's sex. *Source.* Own elaboration based on social security records.

Parental earning

As we described in the section 2.3, unlike previous papers we use the maximum earnings between parents as a measure of parental permanent income. Most of the previous paper uses the father's earning or family income. We adopted this criterion due to data availability. However, Leites et al. (2021) explore the implications of that decision to measure intergenerational income mobility using Uruguayan Tax Authority records and a more reduced period (2009-2016). They suggest that the results do not change much when they use alternative criteria to define parental income and they use alternative samples. In this study, we use an alternative database and we consider a larger period to take into account the tendency between cohorts. Part of the results found may be due to the decision to use the maximum earnings between parents as a measure of permanent income, instead of the father's earnings (or other statistics). This could affect our estimates because the participation of fathers is relatively low in the first 5 cohorts. As a robust check, we analyse the potential effect of this issue on our IRA estimates based on equation 2. In this case, we performed regressions according to the sex of the parents. The estimates are based on three age-grouped cohorts in order to have a sufficient number of observations, leaving the last year (1981) as a group by itself.

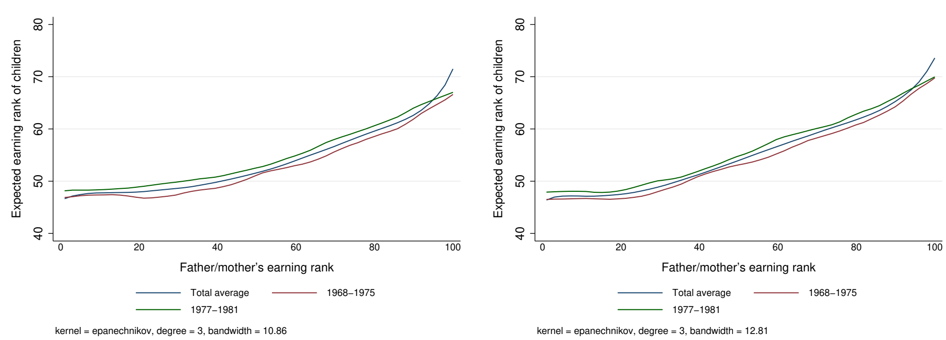
Figure B.6 summarises these results. It suggests that the IRA is higher when the mothers' earnings are used than when the father's earnings are. However, this gap is found for the older cohorts, and the IRA based on fathers or mothers tends to converge for the more recent cohorts. Regarding the tendency, the results support the decline in intergenerational earning mobility and are consistent with the previous results.

3.2 | Results: Intergenerational persistence and directional mobility

The previous section provides summary measure of intergenerational mobility by cohort. In this section, we provide complementary measures to describe the nature and direction of intergenerational mobility.

First, we explore the expected ranking of the children based on age 30-34, conditional on parents' ranking, which provides a more complete viewpoint of intergenerational mobility. Panels a and b in Figure 9 show the estimation of a kernel-weighted polynomial regression for our two alternative measures of permanent earning. The former depicts the minimum expected permanent earning (5-years average includes zeros), while the second Figure depicts the maximum expected permanent earning (5-years average excludes zeros). Note that this strategy provides non-linear estimates of the curves presented in the examples of Figure 3. In all cases, we use the global earning distribution as reference. [19] In each case, blue line presents the expected percentile for the average of all cohorts grouped, red line represents the 1968-1975 cohorts grouped and the green line the 1977-1981 cohorts grouped. The criteria for grouping the cohorts is based on the results reported in Figure 4 and the changes observed in the IRA coefficients, where the IRA of the first group of cohorts is lower than the IRA of the second group of cohorts.

As both panels show, the expected ranking of the children based on average cohorts suggests a convex relationship with a more steep slope in the top of the distribution in the case of Panel a. This result is consistent with the findings of Nybom and Stuhler (2017) for Sweden. The evidence regarding the differences between cohorts suggests a similar shape, but different magnitudes. Those cohorts that report a higher IRA, also tend to show a higher conditional expected ranking of the children given parents' percentiles. These results (mainly those from the panel a in Figure 9 are in agreement with the increase in absolute mobility presented above but do not provide conclusive results with respect to relative mobility.



(a) Permanent income includes zeros (b) Permanent income excludes zeros

FIGURA 9 Expected percentile of earning rank of sons based on parent's earning rank. Global earning distribution. *Notes:* Cohorts when child is aged 30 to 34. The dependent variable is average offspring percentiles rank. Children and Parent percentiles based on global earning distribution for each generation. Estimates based on non-parametric methods, over 100,850 observations. *Source:* Own elaboration based on social security records.

Finally, we supplement our previous analysis by considering an alternative statistic that directly measures the child's chances of persistence and the probability of upward mobility. Figures 10 and 11 present alternative transition probabilities for the 1966-1981 birth cohorts

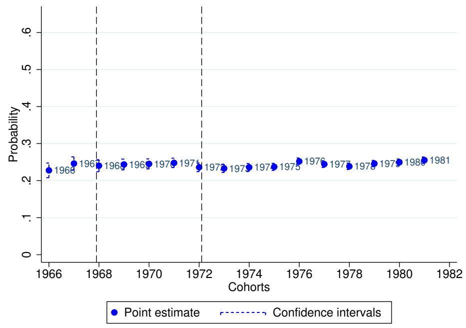
[19]The results remain qualitatively the same when we consider the distribution on the own sample (see Figure B.7 in the Appendix)

using the children at ages 30-34. The former and the second Figures present lower and upper bounds versions of or permanent earning measures respectively. Both cases consider the global earning distribution as a reference.

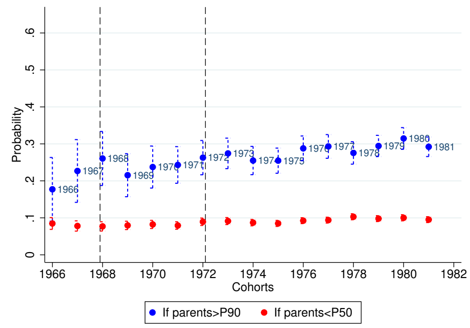
In each case Panel (a) presents a measure of the degree of persistence (children persistence transition-PT). Panel (b) presents the upward transition probability (UM_0), which represents the probability that the child exceeded in the child's generation the parents' position in their generation. Panel (c) presents a more demanding measure of upward transition. In this case, it identifies the probability that the child's ranking in the distribution of its generation exceeds in 5 positions the parent ranking in the prior generation (UM_5). Finally, Panel (d) compares the chance for two groups of children to reach the top-earning decile. On the one hand, it reports $\mathsf{UTP}_c^{40,50}$ which represents the probability that a child reaches the top decile in the child's generation conditional to parent earning being in the bottom half of the distribution of her/his generation. On the other hand, it reports the probability for a child to stay in the top decile, given that their parents are at the top decile.

Panel (a) suggests that our measure of intergenerational persistence (PT) is relatively stable for the 1966-1977 birth cohorts. However a small increase in persistence is observed for the cohorts that faced the crisis when they were between 30 and 34 years old (1968-1972 birth cohorts). Panel (b) and Panel (c) suggest that the child's chance of moving up in the income distribution relative to her parents is relatively stable but is a bit lower for the more recent cohorts. This tendency is more clear in Figure 11, in which the (UM_0) decreases from 0.74 for those cohorts born before 1978, to 0.68 for the birth cohort 1981. In the case of UM_5 the probability declines from 0.67 to 0.62. Although the evolution of average relative mobility is not expected to have a direct relationship with directional mobility trends, in this case, this tendency seem to be consistent with the results from section 3.1. Finally, (d) confirms that parental earning is relevant to explain the probability that a child reaches the top decile. When the parents belong to the top decile, this probability is 3 times higher than when the parents belong to the first half of the distribution of their generation. Finally, the chance of these transitions is relatively stable for the 1966-1983 birth cohorts.

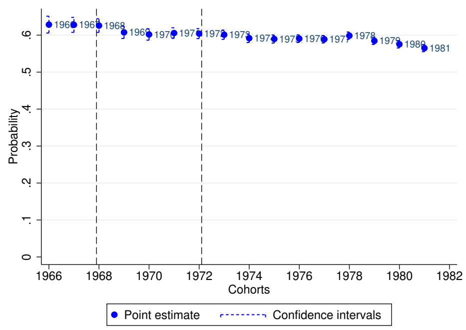
As a robustness check, we replicate the transitions probabilities but when we consider the own sample earning distribution. Figures B.8 and B.9 in the Annex presents the results for the analogous estimates for children from 30 to 34 and 28 to 32 years old respectively. The results remain qualitatively the same.



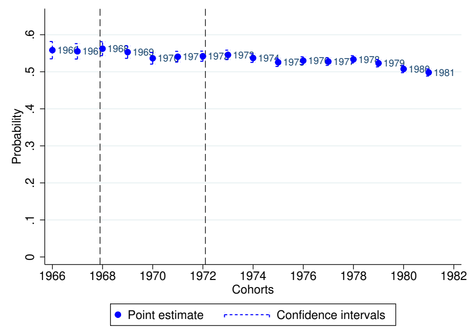
(a) Persistence (+/- 10 percentile than the parents)



(b) Directional Rank Mobility

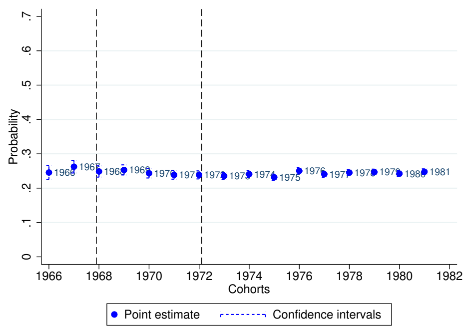


(c) Upward transition probability (+1 percentile)

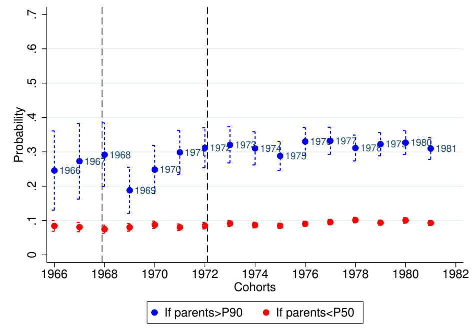


(d) Upward transition probability(+5 percentile)

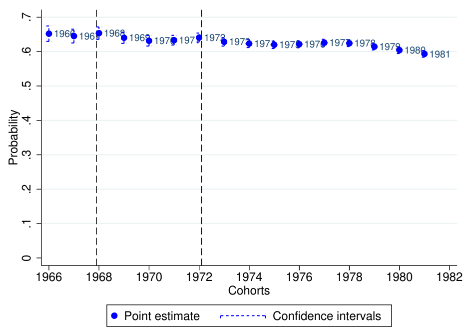
FIGURA 10 Transitions for cohorts when child is aged 30 to 34. Global earning distribution. (5 years average includes zeros). *Notes:* Graph (a) represents the probability that the child belong to the same percentile than their parents or with a difference of +/- 10 percentile. Graph (b) represents the probability that the child exceeded the 90 Percentile when the parents belong to the first half of the distribution of their generation, or when the parents belong to the top Decile of the distribution of their generation. Graph (c) represents the likelihood for an individual to surpass their parent's place in the distribution. Graph (d) represents the likelihood for an individual to surpass their parent's place in the distribution by a amount of 5 positions. Coefficients are OLS estimates, over 100,850 observations. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. *Source:* Own elaboration based on social security records.



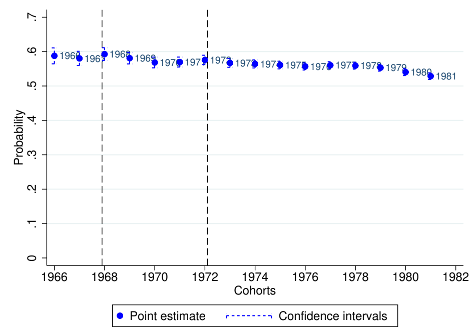
(a) Persistence (+/- 10 percentiles than the parents)



(b) Directional Rank Mobility



(c) Upward transition probability (+1 percentile)



(d) Upward transition probability(+5 percentile)

FIGURA 11 Transitions for cohorts when child is aged 30 to 34. Global earning distribution. (5 years average excludes zeros). *Notes:* Graph (a) represents the probability that the child belong to the same percentile than their parents or with a difference of +/- 10 percentile. Graph (b) represents the probability that the child exceeded the 90 Percentile when the parents belong to the first half of the distribution of their generation, or when the parents belong to the top Decile of the distribution of their generation. Graph (c) represents the likelihood for an individual to surpass their parent's place in the distribution. Graph (d) represents the likelihood for an individual to surpass their parent's place in the distribution by a amount of 5. Coefficients are OLS estimates, over 100,850 observations. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. *Source:* Own elaboration based on social security records.

4 | EFFECT OF THE CRISIS ON INTERGENERATIONAL MOBILITY LEVELS

Our main objective in this section focuses on estimating the potential effects of unemployment events experimented by the household around the 2002 macroeconomic crisis. First, we explore whether there are significant impacts in the short and medium term for the workers directly affected by the negative event in the crisis, and then focus on intergenerational outcomes. As in the previous section, the analysis focuses on the effects related to formal jobs and does not address informality [20]

[20] The informal sector may buffers the loss of work produced by the economic cycle.

4.1 | First stage: 2002 crisis effect on parents generation

As a first approximation to the effects of the adverse event on earnings, we show in Figure 12 the evolution of income before and after the event for our treatment and control groups. We include as treated the group of workers between 45 and 65 years old that perceive unemployment insurance benefits around the 2002 crisis. In the control group, on the other hand, we include the set of workers who did not experience separations with the labor market around the crisis.

In the period of largest impact of the crisis on the labor market, both groups of workers register decreases in their real wages. However, the extent of the decline is substantially larger for the treatment group, with a drop of approximately 30 % in the first quarter after the unemployment event. The decline in control group wages is significantly lower, potentially explained by the inflation process in the period and not by a reduction in the nominal income for these workers. Starting in the third quarter after the shock, workers face a fast recovery of earnings up to approximately six quarters. From that moment on, the growth rate of wages diminishes, and earnings do not recover the level they had 3 years before the shock. This pattern of recovery is similar to previous evidence for developed countries (Oreopoulos et al., 2008; Jacobson et al., 1993; Couch and Placzek, 2010), and in particular to that found by Amarante et al. (2013) for Uruguay.

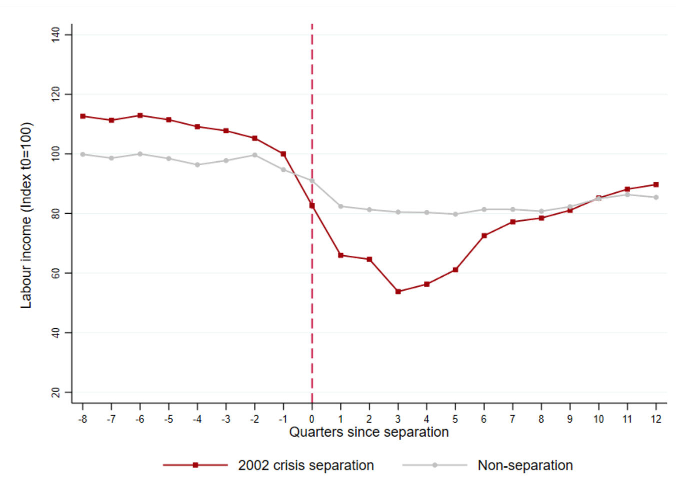


FIGURA 12 Evolution of labor incomes before and after the unemployment event (treated vs control workers). *Notes:* The treatment group include the set of workers with unemployment event between june of 2002 and july of 2003. The control group is the set of workers without a separation in the period. *Source:* Own elaboration based on social security records.

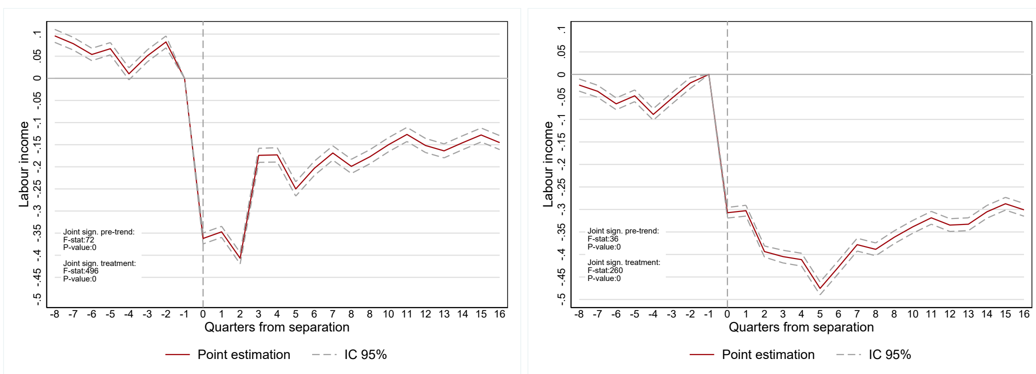
In section 3.1, we discussed the results for a sub-sample of parent-sons pairs for whom it is possible to recover their permanent income. In Figure B.10, we replicate the results of the Figure 12 but only including the parents that belong to this sub-sample. The earnings pattern is analogous to the previous one for control and treatment groups. Again treated individuals show a larger reduction in their wages, particularly in the first year after the shock.

A potential concern for our identification strategy is the decline in income experienced before the event. These pre-shock trends may be a challenge for the identification strategy, pointing to a possible selection of workers laid off by firms, even in the type of macroeconomic shock that we are analyzing.

As we mentioned in the section 2.4.3, the use of individual fixed effects allows us to mitigate the possible biases caused by the presence of selection at the time of the dismissals. The Figure 13 shows the main results for the panel event-study model (equation 10). The coefficients represent the effect of the treatment vs control group against the quarter prior to the unemployment shock (leads and lags in the equation 10). Panel (a) specification includes worker characteristics (gender, age, and job characteristics) and time-fixed effects. Our preferred specification, which incorporates individual fixed effects, is presented in Panel (b).

In both specifications, a negative and significant effect is observed due to the shock, which reduces income between 40 % and 50 % in the first quarter after the unemployment insurance event. The following quarters show a recovery of labor incomes, but without reaching the levels prior to the shock in the following 3 years (the level of wages remains close to 30 % below the pre-event levels).

Regarding the identification strategy, a clear trend before the shock is not observed, however, the set of coefficients corresponding to lags are significant ($\mathtt{Lags}_k$ coefficients). However, the strong negative effects and their persistence over time suggest that the unemployment event had consequences on the income path of the affected workers.[21]



(a) Time fixed effects

(b) Time and individual fixed effects

FIGURA 13 Effect of unemployment event on parents' generation (panel event-study estimation). *Notes:* The Figure shows the estimation of the equation 10. The treatment group include the set of workers with unemployment event between june of 2002 and july of 2003. The control group is the set of workers without a separation in the period. Panel (a) include time fixed effects and panel (b) include time and individual fixed effects. *Source:* Own elaboration based on social security records.

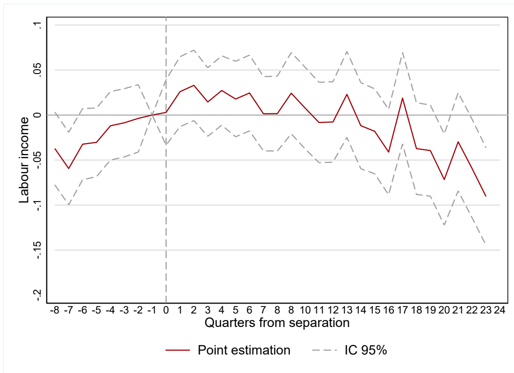
4.2 | Effects on second generation

The effects of the 2002 crisis for the treated workers may have consequences for other members of the household through several channels: lower investments in human capital, weaker networks and transmission of employers, early entries into the labor market (the typical added work effect related with household's survival strategies). Next, we explore if these channels work in our case, and part of the shock experienced by the household is transferred to the second generation.

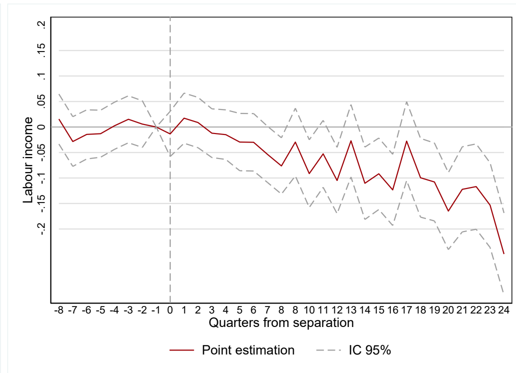
First, we explore the effects of the shock on the path of earnings of the second generation in their first years of activity in the labor market. Because insertion into the labor market can

[21] An additional identification strategy will be explored, exploiting the unemployment events caused by the closure of firms, which potentially has a greater degree of exogeneity than the set of unemployment events due to the 2002 crisis.

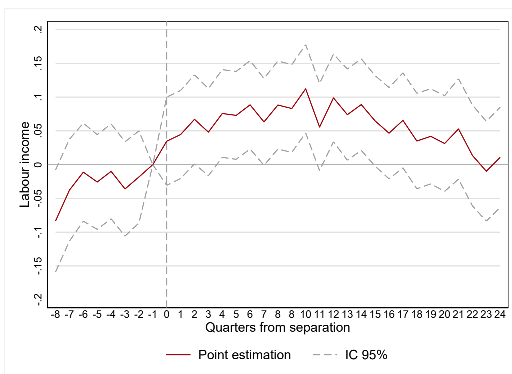
have long-lasting consequences on future income trajectories, the shock in the household could advance the moment of entry to the labor market for a group of sons or daughters, or increase the propensity to accept lower-income jobs to mitigate the effects of the adverse shock at the household level.



(a) Average effect (sons between 10 and 30 years old at the moment of the shock



(b) Sons between 10 and 20 years old at the moment of the shock



(c) Sons between 20 and 30 years old at the moment of the shock

FIGURA 14 Effect of unemployment event on second generation current incomes (panel event-study estimation). First years of activity in labour market *Notes:* The treatment group is the set of children with parents who experienced an unemployment event. The control group is the set of sons without shocks at the household level. Time 0 in normalised to the period when individuals turn 25 years old. Panel (a) include the set of sons from households in the treatment or control groups. Panel (b) include the set of sons below 20 years old at the moment of the shock. Panel (c) include the set of sons above 20 years old at the moment of the shock. *Source:* Own elaboration based on social security records.

Figure 14 shows the evolution of earnings for the sons generation. We use a model similar to the equation 10 with three important modifications. First, our variable of interest is the current income of the younger generation. Second, the treatment group is defined by the shock received by the parents in the 2002 crisis, and not directly by the individuals analyzed. Finally, to analyze the income trajectory in the first years of work activity, we establish moment zero as the period when young people turn 25 years old.

Panel (a) of the Figure 14 shows the effects on current income for the set of children with parents in the control or treatment groups used in the section 4.1. For the average generation of children, no significant differences are observed, at least until they approach 30 years of age (20 quarters after the time set as the 0 periods).

In panels (b) and (c) we present the same results but divide the sample according to the moment when their parents experienced the shock. Since it is expected that the main effects for the second generation of an adverse event at the household level are concentrated in the younger ages, we split the children taking into account whether they were under or over 20 years old at the time of the shock. The results of Panel (b) suggest that the group of children that were younger at the time of the crisis presents a growing gap between the group of treated and controls over time. This implies that the shock at the household level has effects on current income trajectories in the second generation. These results contributes evidence to answer the research question 2 raised in section 1.

Finally, we explore the possibility that the macroeconomic shock has an impact on the permanent income of the second generation, and potentially on the intergenerational income transmission mechanism (equation 12 of the empirical strategy). Table 2 report the treatment effects on the permanent income of children. The model is estimated for three definitions of permanent income, depending on the age used for its measurement: 24 to 28 (columns 1 to 3), 28 to 32 (columns 4 to 6), and 30 to 34 (columns 7 to 9). In this case, we incorporate earlier ages in the life cycle in the estimate, to include cohorts of children who suffered the crisis before entering the labor market. As we discussed in the methodological section, the potential life cycle biases when incorporating earlier ages can be mitigated if we assume that these biases are similar between the treated and control groups. Table 2 presents the results for an approximation of permanent income through rankings. While in Table A.3 in the appendix the estimates for the logarithm of income of parents and children are replicated.

CUADRO 2 Effect of unemployment event on the permanent income of children (treatment vs control households).

	Age group: 24-28			*Age group: 28-32*			*Age group: 30-34*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment 2002	-3.579***	-0.138	0.913	-5.417***	-0.816*	0.772	-5.274***	-0.470	2.207**
	(0.307)	(0.314)	(0.683)	(0.422)	(0.429)	(0.887)	(0.517)	(0.521)	(1.050)
Parents Ranking		0.186***	0.189***		0.229***	0.233***		0.235***	0.240***
		(0.00407)	(0.00432)		(0.00518)	(0.00544)		(0.00593)	(0.00618)
Parents Ranking*Treat			-0.0218*			-0.0351**			-0.0620***
			(0.0127)			(0.0173)			(0.0211)
Son's age and cohort	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parents sex and age		✓	✓		✓	✓		✓	✓
Observations	88,567	88,535	88,535	56,779	56,768	56,768	42,652	42,645	42,645
R-squared	0.013	0.037	0.037	0.007	0.044	0.044	0.009	0.050	0.050

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable is the permanent income of the children measured in three age groups (24-28, 28-32, and 30-34). The estimation is based on the equation 12. The first specification only includes the treatment effect (columns (1), (4) and (7)), the second specification controls for the permanent income of the parents (columns (2), (5) and (8)), while the third specification incorporates an interaction between the treatment and the income of the parent generation (columns (3), (6) and (9)). *Source:* Own computations based on social security records.

The first specification only includes the effect of treatment on the permanent income of the children (columns (1), (4), and (7) of Table 2). In all cases the effect is negative and significant, suggesting that the negative shock experienced by the parents is carried over to the next generation. However, part of the effects of the shock suffered by the household may be transmitted through the permanent income of the parents.

In the second specification, we include the permanent income of the parents as control. As observed in columns (2), (5), and (8) the coefficient for this income gives us an approximation to the level of intergenerational persistence for the subgroup of controls and treats used in these estimates (parameter β in the equation 12). In all cases, it is between 0.19 and 0.23 depending on the age range, similar levels to those reported in the first section of results (section 3.1). The coefficient of interest shows a negative effect, although in this case, not significant (the exception is the coefficient for the 28-32 age group, which is statistically significant at 10 %).

The last specification of the model incorporates the potential effect of the adverse event on the intergenerational transmission (parameter θ_c in the equation 12). As observed in columns (3), (6), and (9), the interaction shows a negative and significant effect. In this sense, the consequences of the shock at the household level seem to be transferred to the second generation but mediated by the mechanisms of intergenerational transmission of income.The joint reading of the estimated parameters suggested that the effect of the crisis on intergenerational transmission is concentrated in children from households located in the middle and upper part of the distribution.

The results, provide evidence to answer the research question 3, suggest a reduction in the levels of intergenerational persistence due to the macroeconomic crisis. There are diverse explanations for this increase in intergenerational mobility. First, the macroeconomic shock could destroy part of the social capital and networks of the workers, mitigating one of the channels of intergenerational transmission of income. On the other hand, the composition of those affected by the crisis could have a role in the observed result. Given that lower-income households are less likely to reduce their position in the income distribution (they are already in the lower tail of the distribution), the result may reflect a loss of income from the middle or upper-middle strata due to the adverse event. The sons of treated households in these middle strata lose expected income due to the shock, which translates into less intergenerational persistence.

A possible concern of the previous estimates is the imbalance in the sex of the parents between treated and controls.[22] The levels of intergenerational mobility show differences by sex (see Figure B.6 in the annex), so the treatment effect could capture part of a composition effect.

We follow two complementary strategies to mitigate the potential consequences of this imbalance. First, on Table 3 we estimate the model independently for fathers and mothers. The first specification (columns (1), (4), and (7)) confirm a direct and negative effect of treatment on the permanent income of the children. The magnitude of the effect is similar when the unemployment event refers to fathers or mothers. However, we found relevant differences when incorporating the parents' income as part of the model. Although the parameter of intergenerational persistence (parameter β in the equation 12) is similar for fathers and mothers, the effect of unemployment on children's' permanent income seems to depend on which parent was affect by the shock. The treatment effect continues to be negative and significant when incorporating only fathers on all the specifications and age groups (Columns (2), (5) and (8) in Panel A). On the other hand, in the case of mothers (Panel B), the treatment effect disappears as in our average estimates but observing a significant effect in the intergenerational income transmission mechanism (interaction between treatment and the permanent income of the parents). The differential effects of mothers and fathers unemployment on the permanent income of the children could be associated with the feature that the role of "secondary worker"still prevails among most women [23] More analysis is needed to interpret these differences.

[22] For example, in the estimates for the 28 to 32-year-old age bracket, the proportion of male parents is approximately 40 % for those treated, but less than 20 % for the control group.

[23] For the analysed generations of mothers, women with low and medium education in Uruguay tend to follow

CUADRO 3 Effect of unemployment event on the permanent income of children by sex of parents (treatment vs control households).

	Age group: 24-28			Age group: 28-32			Age group: 30-34		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Fathers									
Unemployment 2002	-3.506***	-1.034**	-0.485	-4.420***	-1.764**	-0.738	-5.420***	-3.208***	-3.965
	(0.421)	(0.422)	(1.019)	(0.691)	(0.692)	(1.614)	(1.060)	(1.055)	(2.509)
Parents Ranking		0.206***	0.208***		0.228***	0.231***		0.203***	0.201***
		(0.00682)	(0.00756)		(0.0111)	(0.0123)		(0.0168)	(0.0184)
Parents Ranking*Treat			-0.0102			-0.0196			0.0293
			(0.0175)			(0.0284)			(0.0414)
Observations	29,971	29,961	29,961	11,774	11,773	11,773	5,269	5,268	5,268
R-squared	0.036	0.066	0.066	0.027	0.062	0.062	0.025	0.054	0.054
Panel A: Mothers									
Unemployment 2002	-2.664***	0.868*	2.288**	-4.602***	-0.292	1.311	-4.064***	0.326	3.316***
	(0.459)	(0.465)	(0.945)	(0.539)	(0.544)	(1.081)	(0.593)	(0.598)	(1.142)
Parents Ranking		0.179***	0.182***		0.232***	0.234***		0.241***	0.245***
		(0.00507)	(0.00525)		(0.00586)	(0.00607)		(0.00634)	(0.00656)
Parents Ranking*Treat			-0.0337*			-0.0389*			-0.0685***
			(0.0197)			(0.0228)			(0.0248)
Observations	58,585	58,574	58,574	45,003	44,995	44,995	37,382	37,377	37,377
R-squared	0.008	0.028	0.028	0.006	0.039	0.039	0.008	0.045	0.045
Son's age and cohort	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parents sex and age		✓	✓		✓	✓		✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the permanent income of the children measured in three age groups (24-28, 28-32, and 30-34). The estimation is based on the equation 12. Panel A include only fathers and Panel B mothers. The first specification only includes the treatment effect (columns (1), (4) and (7)), the second specification controls for the permanent income of the parents (columns (2), (5) and (8)), while the third specification incorporates an interaction between the treatment and the income of the parent generation (columns (3), (6) and (9)). *Source:* Own computations based on social security records.

As a second strategy, we selected a sample of controls based on the characteristics of the parents prior to shock (Table A.4).[24] The main difference with respect to the average results presented in Table 2 is that, in this case, the treatment effect is not significant. However, this could be explained by the reduction in the number of observations when selecting a sub-sample of controls.

Finally, we evaluate if this average effect may conceal significant impacts according to the age at which the generation of children suffered the impact. The shock in the household can have stronger consequences if it affects the investments in education and human capital that the household makes in the younger generation. Additionally, it can affect the moment in which young people enter the labor market, affecting their future income trajectories. Both effects would be concentrated in cohorts of children affected by the crisis in ages under or close to 20 years.

Figure 15 shows the results for different cohorts of children. As expected, the negative results of treatment seem to be concentrated in the younger sons at the time of shock (15-18 and 19-22), however, the results are not significant. Again, the imprecise estimation could be

a secondary labor force behavior (Espino et al., 2017)

[24]We construct a sub-sample from the nearest neighbour method including age, sex, income prior to the shock, and employment characteristics as co-variables.

due to the low number of observations when working with sub-samples of our treatment and control groups.

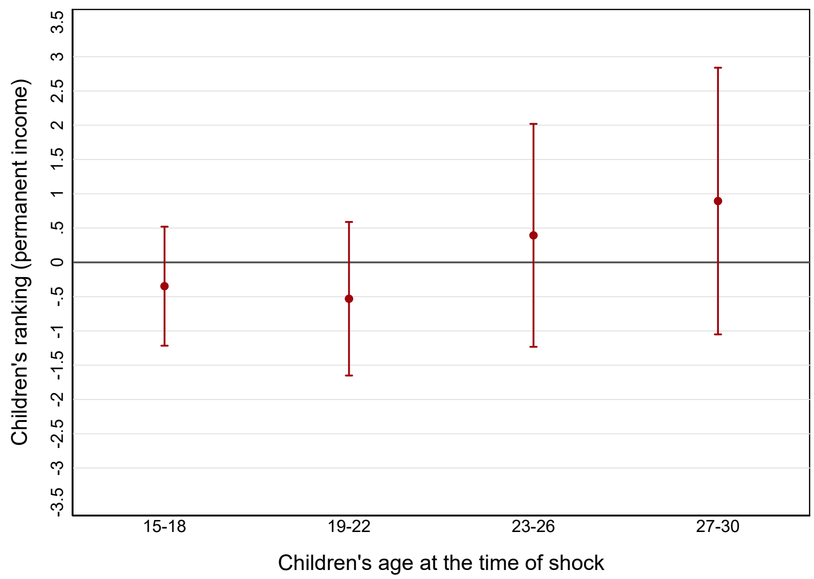


FIGURA 15 Effect of unemployment event on the permanent income of children by sons cohorts (treatment vs control households). *Notes:* The dependent variable is the permanent income of the children measured in in four groups according to their age at the time of shock (15-18, 19-22, 23-26 and 27-30). The estimation is based on the equation 12. The specification includes permanent income of the parents as a control. *Source:* Own computations based on social security records.

5 | FINAL COMMENTS

The average IRA estimates for children at ages 30-34 is between 0.20 and 0.25. This is in line with previous studies available for Uruguay and in the international context, it places Uruguay in an intermediate place in terms of the degree of intergenerational mobility. The results suggest a heterogeneity on the degree of intergenerational earning mobility across birth cohorts.

Like in previous studies for other countries, our results regarding trends are very sensitive to the measure of intergenerational mobility that is considered. In particular, when we estimate the IRA for each cohort, the tendency depends on the specification considered and the inclusion of intercepts by cohorts. Concerning absolute mobility, the alternative strategies indicate a higher mobility for the later cohorts. We find a consistent pattern to these results when incorporating the life cycle, the sex of the children, and alternative criteria to define the income of the parents.

The estimates that incorporate an identification strategy to derive the effects of the macro shock show, in the first place, negative and significant impacts on the income of the affected workers (parents with unemployment events), mainly concentrated in the first year after the event but which persist in the med-term.These significant effects allowed us to advance in the potential transmission of this shock between generations.

The shock experienced by the parents has a negative and significant effect on the next generation. However, the magnitude of the effect depends on the position of the parents and the age of the children at the moment of the shock. The differences regarding the age of the children could be related with loses in specific human capital investment and the conditions of entry in the labor market.

On the other hand, the results suggest that the effects in the second generation are greater for those children whose parents are located in the middle and upper part of the income distribution. This could be consistent with the fact that the adverse shock faced by parents decreases the social capital, networks and specific capital of families. But also, this could be explained by a mechanical effect due to the fact that the relative mobility is higher in the lower part of the distribution. Finally, the results suggest that the IRA is slightly lower for families in with the parents lost their jobs compared with those families whose parents keep their job.

Further robustness checks are expected in the future to confirm the validity of the results about the intergenerational transmission of the shock produced by the 2002 crisis. On the one hand, we will consider alternative control groups that have similar characteristics but whose earning has not been affected by the macroeconomic crisis (e.g. public employers). Second, we would consider as an exogenous shock the parents who lost their jobs due to the closure of firms in 2002.

The results are relevant to understand the intergenerational persistence of earnings inequality. The shock experienced by the parents has a negative and significant effect on the next generation. Evidence suggests possible labor market mechanisms that affect levels of intergenerational transmission. The position of the household at the time of facing the shock, and the age of the children at the time of the event are relevant to determine the magnitude of the negative effect. This has an important relevance to mitigate the consequences of macroeconomic crises, and reduce the negative effects in the medium and long term.

ACKNOWLEDGEMENTS

We thank Jan Sthuler, Ernesto Eschargrodsky, Maria Berniell, María De La Mata and participants in Academic Workshop RED 2022 (CAF) and LACEA-LAMES 2021 for helpful comments. We would also like to express our thanks to Development Bank of Latin America (CAF) for selecting this proposal in the call for research projects on Intergenerational Mobility in Latin America and for financial support.

REFERENCIAS

Aghion, P., Banerjee, A. and Piketty, T. (1999) Dualism and macroeconomic volatility. *The Quarterly Journal of Economics*, **114**, 1359–1397.

Amarante, V., Arim, R. and Dean, A. (2013) Unemployment insurance design and its effects: Evidence for Uruguay. *Revista Desarrollo y Sociedad*, 7–42.

— (2014) The effects of being out of the labor market on subsequent wages: evidence for Uruguay. *Journal of Labor Research*, **35**, 39–62.

Bjorklund, A. and Jantti, M. (1997) Intergenerational Income Mobility in Sweden Compared to the United States. *American Economic Review*, **87**, 1009–18.

Björklund, A., Jäntti, M. and Lindquist, M. J. (2009) Family background and income during the rise of the welfare state: Brother correlations in income for swedish men born 1932-1968. *Journal of Public Economics*, **93**, 671–680.

Björklund, A., Roine, J. and Waldenstöm, D. (2012) Intergenerational top income mobility in Sweden: Capitalist dynasties in the land of equal opportunity?. *Journal of Public Economics*, **96**, 474–484.

Blanden, J., Goodman, A., Gregg, P. and Machin, S. (2005) Changes in intergenerational, income mobility in britain. In *Generational Income Mobility in North America and Europe* (ed. M. Corak), chap. Generational Income Mobility in North America and Europe, 102–138. Cambridge University Press, Cambridge.

Bourguignon, F., Ferreira, F. and Walton, M. (2007) Equity, efficiency and inequality traps: A research agenda. *The Journal of Economic Inequality*, **5**, 235–256.

Bratberg, E., Nilsen, Ø. A. and Vaage, K. (2005) Intergenerational earnings mobility in norway: Levels and trends. *The Scandinavian Journal of Economics*, **107**, 419–435.

— (2008) Job losses and child outcomes. *Labour Economics*, **15**, 591–603.

Breen, R. and García-Peñalosa, C. (2005) Income inequality and macroeconomic volatility: an empirical investigation. *Review of Development Economics*, **9**, 380–398.

Callaway, B. and Sant'Anna, P. H. (2021) Difference-in-differences with multiple time periods. *Journal of Econometrics*, **225**, 200–230.

Carneiro, P. and Heckman, J. J. (2002) The evidence on credit constraints in post-secondary schooling*. *The Economic Journal*, **112**, 705–734.

Carrasco, P., Cichevski, A. and Perazzo, I. (2018) Evolución reciente de las principales variables del mercado laboral uruguayo. *Tech. rep.*, Serie Documentos de Trabajo, DT 09/18. Instituto de Economía, Facultad de Ciencias Económicas y Administración, Universidad de la República, Uruguay. URL: http://www.iecon.ccee.edu.uy/dt-09-18-evolucion-reciente-de-las-principales-variables-del-mercado-laboral-uruguayo/publicacion/627/es/.

Chen, L., Gordanier, J. and Ozturk, O. D. (2017) Following (not quite) in your father's footsteps: Task followers and labor market outcomes. *Available at SSRN 2894978*.

Chetty, R., Grusky, D., Hell, M., Hendren, N., Manduca, R. and Narang, J. (2017) The fading american dream: Trends in absolute income mobility since 1940. *Science*, **356**, 398–406.

Chetty, R. and Hendren, N. (2018) The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects. *The Quarterly Journal of Economics*, **133**, 1107–1162.

Chetty, R., Hendren, N., Kline, P. and Saez, E. (2014a) Where is the land of opportunity? The geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics*, **129**, 1553–1623.

Chetty, R., Hendren, N., Kline, P., Saez, E. and Turner, N. (2014b) Is the United States still a land of opportunity? Recent trends in intergenerational mobility. *American Economic Review*, **104**, 141–47.

Clarke, D. and Schythe, K. (2020) Implementing the panel event study. *IZA Discussion Paper*. URL: https://ftp.iza.org/dp13524.pdf.

Cleveland, W. S., Devlin, S. J. and Grosse, E. (1988) Regression by local fitting: methods, properties, and computational algorithms. *Journal of econometrics*, **37**, 87–114.

Corak, M. and Heisz, A. (1999) The intergenerational earnings and income mobility of canadian men: Evidence from longitudinal income tax data. *Journal of Human Resources*, 504–533.

Corak, M., Lindquist, M. J. and Mazumder, B. (2014) A comparison of upward and downward intergenerational mobility in Canada, Sweden and the United States. *Labour Economics*, **30**, 185–200.

Corak, M. and Piraino, P. (2010) Intergenerational earnings mobility and the inheritance of employers. *IZA Discussion paper*.

Couch, K. A. and Placzek, D. W. (1997) Notes on tuition sensitivity in the Becker-Tomes model. *unpublished manuscript, University of Chicago*.

— (2010) Earnings losses of displaced workers revisited. *American Economic Review*, **100**, 572–89.

Dahl, M. and DeLeire, T. (2008) The association between children's earnings and fathers' lifetime earnings: Estimates using administrative data. *Discussion Paper No. 1342-08. Institute for Research on Poverty, University of Wisconsin-Madison*.

Daude, C. and Robano, V. (2015) On intergenerational (im)mobility in Latin America. *Latin American Economic Review*, **24**, 9.

Davis, J. and Mazumder, B. (2020) The decline in intergenerational mobility after 1980. URL: osf.io/preprints/socarxiv/evfcx.

Dunn, C. E. (2007) The intergenerational transmission of lifetime earnings: Evidence from brazil. *The BE Journal of Economic Analysis & Policy*, **7**.

Díaz, J. D., Gutiérrez, P., Troncoso, P. and Villarroel, G. I. (2021) Intergenerational Earnings Mobility in Chile: A tale of two tails. *unpublished manuscript*. URL: http://www.ecineq.org/wp-content/uploads/papers_EcineqLSE/EcineqLSE-248.pdf.

Espino, A., Isabella, F., Leites, M. and Machado, A. (2017) Do women have different labor supply behaviors? evidence based on educational groups in uruguay. *Feminist Economics*, **23**, 143–169.

Freyaldenhoven, S., Hansen, C. and Shapiro, J. M. (2019) Pre-event trends in the panel event-study design. *American Economic Review*, **109**, 3307–38.

Haider, S. and Solon, G. (2006) Life-cycle variation in the association between current and lifetime earnings. *American Economic Review*, **96**, 1308–1320.

Hertz, T. (2009) *Chapter Five. Rags, Riches, and Race*. Princeton University Press. URL: https://doi.org/10.1515/9781400835492.165.

Huttunen, K. and Riukula, K. (2019) Parental job loss and children's careers. *Tech. rep.*, IZA Discussion Papers.

Jacobson, L. S., LaLonde, R. J. and Sullivan, D. G. (1993) Earnings losses of displaced workers. *The American economic review*, 685–709.

Jiménez, M. (2018) La movilidad intergeneracional del ingreso y sus métodos de estimación. un análisis comparativo para Argentina y Chile. *Cuadernos de Economía*, **41**, 79–103.

Jäntti, M. and Jenkins, S. P. (2015) Chapter 10 - income mobility. In *Handbook of Income Distribution* (eds. A. B. Atkinson and F. Bourguignon), vol. 2 of *Handbook of Income Distribution*, 807–935. Elsevier.

Kramarz, F. and Skans, O. N. (2014) When strong ties are strong: Networks and youth labour market entry. *Review of Economic Studies*, **81**, 1164–1200.

Leites, M., Rivero, L., Salas, G., Suarez, L. and Vigorito, A. (2018) Trayectorias educativas y laborales de los jóvenes en Uruguay. In *Millennials en América Latina y el Caribe: ¿Trabajar o estudiar?* (eds. R. Novella, A. Repetto, C. Robino and G. Rucci). Iadb edn.

Leites, M., Sena, E. and Vila, J. (2020) *Movilidad intergeneracional de ingresos en Uruguay. Una mirada en base a registros administrativos*. Cuaderno sobre Desarrollo Humano N°12 del PNUD, Serie El Futuro en Foco.

Leites, M., Xavier, R., Cecilia, R. and Joan, V. (2021) Intergenerational mobility and top income persistence for a developing country: Estimates using administrative data from uruguay. *unpublished manuscript*.

Manduca, R., Hell, M., Adermon, A., Blanden, J., Bratberg, E., Gielen, A. C., Gielen, A. C., van Kippersluis, H., Lee, K. B., Machin, S. J., Munk, M., Nybom, M., Ostrovsky, Y., Rahman, S. and Sirniö, O. (2020) Trends in Absolute Income Mobility in North America and Europe. *Tech. rep.*, Available at SSRN:. URL: https://ssrn.com/abstract=3648796orhttp://dx.doi.org/10.2139/ssrn.3648796.

Mazumder, B. (2005) Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data. *The Review of Economics and Statistics*, **87**, 235–255.

— (2015) Estimating the intergenerational elasticity and rank association in the us: Overcoming the current limitations of tax data. *PSN: Income Tax (Topic)*.

Mitnik, P., Bryant, V., Weber, M. and Grusky, D. B. (2015a) New estimates of intergenerational mobility using administrative data.

— (2015b) New estimates of intergenerational mobility using administrative data. *Statistics of Income Division working paper, Internal Revenue Service*.

Munk, M., Bonke, J. and Hussain, M. (2016) Intergenerational top income persistence: Denmark half the size of Sweden. *Economics Letters*, **140**.

Neidhöfer, G., Serrano, J. and Gasparini, L. (2018) Educational inequality and intergenerational mobility in Latin America: A new database. *Journal of Development Economics*, **134**, 329–349.

Nybom, M. and Stuhler, J. (2017) Biases in standard measures of intergenerational income dependence. *Journal of Human Resources*, **52**, 800–825.

Oreopoulos, P., Page, M. and Stevens, A. H. (2008) The intergenerational effects of worker displacement. *Journal of Labor Economics*, **26**, 455–483.

Piketty, T. (2000) Chapter 8 theories of persistent inequality and intergenerational mobility. In *Handbook of Income Distribution* (eds. A. B. Atkinson and F. Bourguignon), vol. 1 of *Handbook of Income Distribution*, 429–476. Elsevier.

Querejeta, M. and Bucheli, M. (2021) Motherhood penalties: the effect of childbirth on women's employment dynamics in a developing country. *Documento de Trabajo/FCS-Decon; 01/21*. URL: https://www.colibri.udelar.edu.uy/jspui/handle/20.500.12008/26530.

Seim, D. (2019) On the incidence and effects of job displacement: Evidence from Sweden. *Labour Economics*, **57**, 131–145.

Solon, G. (1989) Biases in the estimation of intergenerational earnings correlations. *The Review of Economics and Statistics*, 172–174.

— (2002) Cross-country differences in intergenerational earnings mobility. *Journal of Economic Perspectives*, **16**, 59–66.

Verho, J. (2017) Economic crises and unemployment persistence: Analysis of job losses during the finnish 1990s recession. *VATT Institute for Economic Research Working Papers*, **99**.

A | APPENDIX

CUADRO A.1 Recruitment of individuals identified as children with respect to the total of 30-year-old workers. By quantiles of labor income and cohort

	N	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
1996	1760	8,11 %	8,54 %	8,05 %	6,82 %	8,11 %	7,09 %	7,68 %	7,78 %	7,63 %	6,87 %
1997	2235	9,84 %	9,59 %	9,64 %	10,92 %	10,54 %	8,60 %	10,04 %	8,50 %	8,31 %	8,75 %
1998	2705	9,97 %	11,51 %	11,91 %	11,66 %	12,06 %	10,91 %	11,96 %	11,71 %	11,41 %	11,17 %
1999	3422	13,84 %	14,81 %	14,94 %	13,90 %	14,91 %	14,30 %	14,59 %	13,45 %	14,60 %	13,90 %
2000	3909	15,35 %	16,17 %	16,42 %	16,42 %	17,54 %	15,10 %	15,61 %	16,83 %	16,27 %	16,01 %
2001	4560	17,09 %	16,99 %	17,29 %	17,83 %	16,90 %	18,36 %	17,97 %	18,43 %	17,24 %	19,01 %
2002	5158	19,74 %	19,14 %	20,63 %	20,74 %	21,96 %	21,18 %	21,13 %	23,73 %	23,17 %	21,03 %
2003	5926	25,84 %	22,36 %	22,96 %	24,20 %	24,65 %	24,21 %	23,60 %	24,67 %	24,84 %	26,50 %
2004	6925	23,93 %	26,92 %	26,77 %	27,28 %	28,59 %	28,36 %	28,48 %	26,99 %	28,36 %	28,60 %
2005	7757	27,07 %	25,91 %	27,44 %	28,72 %	29,02 %	27,33 %	28,42 %	29,43 %	30,03 %	29,76 %
2006	8788	25,96 %	28,08 %	27,95 %	27,99 %	29,59 %	27,28 %	29,06 %	28,79 %	30,47 %	31,44 %
2007	9174	24,89 %	24,74 %	23,84 %	26,14 %	25,71 %	27,93 %	27,02 %	28,33 %	28,89 %	30,63 %
2008	9624	23,40 %	22,43 %	24,10 %	24,60 %	24,88 %	26,14 %	26,00 %	27,78 %	29,40 %	30,33 %
2009	9847	22,96 %	21,52 %	23,86 %	25,94 %	25,94 %	25,20 %	27,05 %	27,93 %	29,32 %	31,49 %
2010	9577	21,63 %	21,47 %	22,32 %	23,12 %	22,62 %	23,51 %	25,40 %	27,34 %	28,02 %	29,88 %
2011	10228	22,06 %	21,49 %	23,91 %	24,17 %	24,14 %	25,43 %	26,46 %	28,07 %	28,62 %	30,96 %

Notes: This table presents the number of children for each cohort and how much they represent from each decile of their respective generation for a specific year. As an example, the 1966 cohort includes all individuals identified as children in the employment history records at age 30 (1996 records). The next cohort, 1967, considers the year 1997, and so on. For the cohorts from 1966 to 1981, it is possible to identify formal incomes between the ages of 30 to 34, for the construction of their permanent income. *Source:* Own elaboration based on social security records.

CUADRO A.2 Statistics by cohort. Age group: 30-34

	Children			*Parents*			*SDp / SDc*
	Mean ranking	Mean income	SD	Mean ranking	Mean income	SD	
1966	44.1	262,776.2	33.09	29.43	210,854.9	21.88	0.66
1967	43.98	261,899	32.27	29.80	153,423.9	22.19	0.69
1968	44.42	258,354	32.65	30.34	157,343.6	22.66	0.69
1969	42.18	232,694.2	32.82	30.58	169,104	22.55	0.69
1970	41.64	217,686.7	32.80	31.27	161,073.7	23.06	0.70
1971	41.78	219,029.4	33.02	32.13	166,254.1	23.12	0.70
1972	42.58	215,304.6	32.57	32.74	178,409.8	23.55	0.72
1973	43.02	222,679.8	32.49	33.02	185,641.6	23.97	0.74
1974	43.93	238,111.6	32.07	33.36	185,101	23.95	0.75
1975	44.90	269,399.8	32.11	34.24	187,047.7	24.24	0.76
1976	46.03	281,484.2	32.10	34.44	190,324.7	24.53	0.76
1977	46.76	305,477.9	32.43	35.24	202,712.3	24.81	0.77
1978	48.09	341,594	32.44	35.71	193,753.1	24.95	0.77
1979	49.16	367,149	32.36	37.04	195,248.2	25.58	0.79
1980	49.46	397,188	31.93	37.55	196,405.7	25.61	0.80
1981	50.15	481,560.2	31.97	38.79	212,570.7	26.26	0.82

Notes: The table presents several statistic measures for each cohort of children aged 30 to 34. Column SDp/SDc refers to the resulting quotient between the standard deviation of parents and the standard deviation of children in each cohort. All estimations are based in global earning distribution. 5 years averages includes zeros. *Source:* Own elaboration based on social security records.

CUADRO A.3 Effect of unemployment event on the permanent income of children by sex of parents (treatment vs control households). Log of permanent income

	Age group: 24-28			*Age group: 28-32*			*Age group: 30-34*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment 2002	-0.167***	-0.0234	0.590***	-0.238***	-0.0378	0.911***	-0.246***	-0.0172	1.310***
	(0.0167)	(0.0172)	(0.158)	(0.0237)	(0.0243)	(0.209)	(0.0299)	(0.0305)	(0.253)
Parents Ranking		0.167***	0.175***		0.208***	0.219***		0.222***	0.236***
		(0.00475)	(0.00515)		(0.00641)	(0.00693)		(0.00769)	(0.00828)
Parents Ranking*Treat			-0.0516***			-0.0807***			-0.114***
			(0.0131)			(0.0175)			(0.0214)
Son's age and cohort	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parents sex and age		✓	✓		✓	✓		✓	✓
Observations	88,567	88,535	88,535	56,779	56,768	56,768	42,652	42,645	42,645
R-squared	0.153	0.166	0.166	0.043	0.064	0.064	0.120	0.143	0.143

Notes: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of permanent income of the children measured in three age groups (24-28, 28-32, and 30-34). The estimation is based on the equation 12. The first specification only includes the treatment effect (columns (1), (4) and (7)), the second specification controls for the permanent income of the parents (columns (2), (5) and (8)), while the third specification incorporates an interaction between the treatment and the income of the parent generation (columns (3), (6) and (9)). *Source:* Own computations based on social security records.

CUADRO A.4 Effect of unemployment event on the permanent income of children by sex of parents (treatment vs control households). Sub-sample of controls by nearest neighbour method

	Age group: 24-28			*Age group: 28-32*			*Age group: 30-34*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment 2002	-0.613	-0.137	1.923**	-0.738	-0.328	-0.354	0.240	0.536	2.771*
	(0.441)	(0.436)	(0.977)	(0.604)	(0.597)	(1.281)	(0.740)	(0.729)	(1.517)
Parents Ranking		0.193***	0.219***		0.199***	0.198***		0.201***	0.232***
		(0.00945)	(0.0145)		(0.0129)	(0.0197)		(0.0160)	(0.0246)
Parents Ranking*Treat			-0.0430**			0.000588			-0.0522*
			(0.0185)			(0.0254)			(0.0315)
Son's age and cohort	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parents sex and age		✓	✓		✓	✓		✓	✓
Observations	18,236	18,236	18,236	9,886	9,886	9,886	6,537	6,537	6,537
R-squared	0.024	0.047	0.047	0.012	0.039	0.039	0.013	0.043	0.044

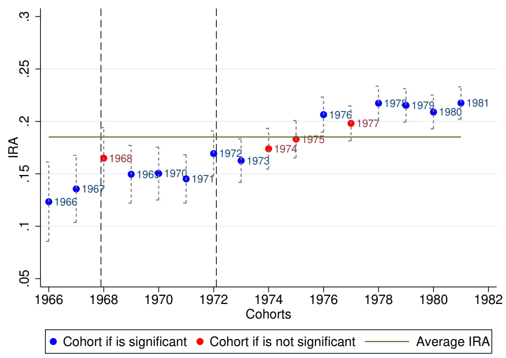
Notes: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the permanent income of the children measured in three age groups (24-28, 28-32, and 30-34). The estimation is based on the equation 12. We include as control group a sub-sample from the nearest neighbour method including age, sex, income prior to the shock,and employment characteristics as co-variables. The first specification only includes the treatment effect (columns (1), (4) and (7)), the second specification controls for the permanent income of the parents (columns (2), (5) and (8)), while the third specification incorporates an interaction between the treatment and the income of the parent generation (columns (3), (6) and (9)). *Source:* Own computations based on social security records.

CUADRO A.5 Effect of unemployment event on the log of permanent income of children by sex of parents (treatment vs control households). Sub-sample of controls by nearest neighbour method

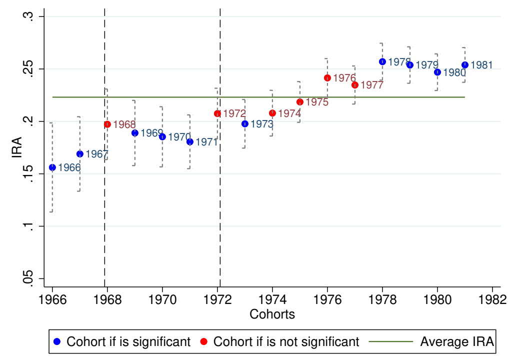
	Age group: 24-28			*Age group: 28-32*			*Age group: 30-34*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment 2002	-0.0238	0.00750	0.671***	-0.0240	0.0117	0.609*	-0.00774	0.0281	1.081**
	(0.0241)	(0.0240)	(0.248)	(0.0343)	(0.0342)	(0.348)	(0.0429)	(0.0427)	(0.436)
Parents Ranking		0.148***	0.185***		0.153***	0.187***		0.151***	0.214***
		(0.0101)	(0.0169)		(0.0139)	(0.0245)		(0.0172)	(0.0314)
Parents Ranking*Treat			-0.0556***			-0.0506*			-0.0899**
			(0.0206)			(0.0291)			(0.0368)
Son's age and cohort	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parents sex and age		✓	✓		✓	✓		✓	✓
Observations	18,236	18,236	18,236	9,886	9,886	9,886	6,537	6,537	6,537
R-squared	0.148	0.159	0.159	0.051	0.065	0.065	0.123	0.138	0.139

Notes: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of permanent income of the children measured in three age groups (24-28, 28-32, and 30-34). The estimation is based on the equation 12. We include as control group a sub-sample from the nearest neighbour method including age, sex, income prior to the shock,and employment characteristics as co-variables. The first specification only includes the treatment effect (columns (1), (4) and (7)), the second specification controls for the permanent income of the parents (columns (2), (5) and (8)), while the third specification incorporates an interaction between the treatment and the income of the parent generation (columns (3), (6) and (9)). *Source:* Own computations based on social security records.

Daughters

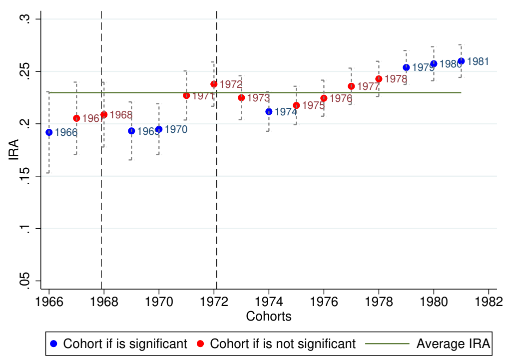


(a) Permanent income includes zeros

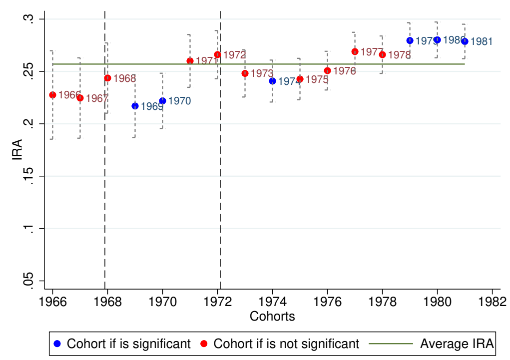


(b) Permanent income excludes zeros

Sons

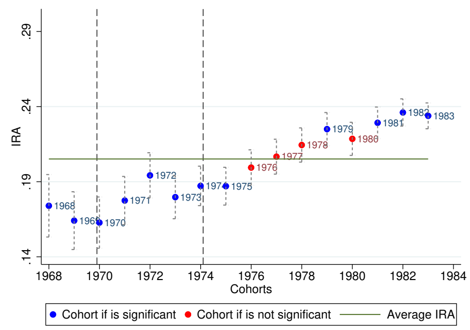


(c) Permanent income includes zeros

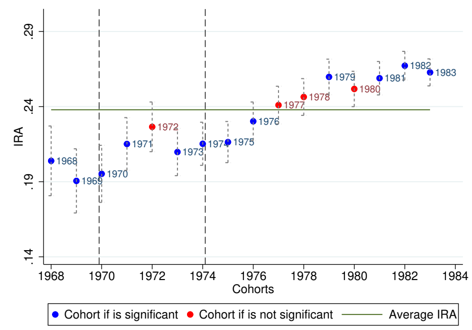


(d) Permanent income excludes zeros

FIGURA B.1 Intergenerational Ranking Association by cohorts when daughters and sons are considered separately. Global earning distribution. *Notes:* Cohorts when child is aged 30 to 34. The dependent variable is the average offspring percentiles rank. Children and Parent percentiles based on own sample earning distribution for each generation. Panel (a) 5-years average includes years with zero earnings. Panel (b) 5-years average includes only years with positive earnings.The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. Coefficients are WLS estimates , over 100,850 observations (52,629 daughters and 48,219 sons). Controls: children's sex, parent's age, and parent's sex. *Source:* Own elaboration based on social security records.

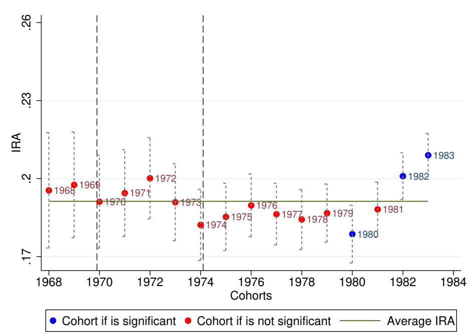


(a) Permanent income includes zeros

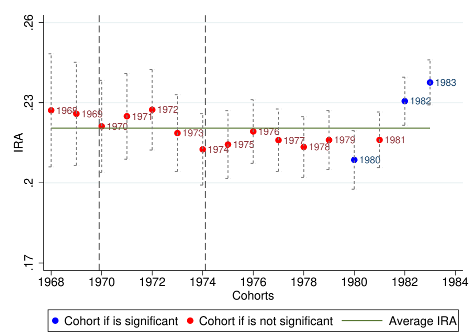


(b) Permanent income excludes zeros

FIGURA B.2 Intergenerational Ranking Association by cohorts. Global earning distribution (cohorts when child is aged 28 to 32). *Notes:* Cohorts when child is aged 28 to 32, parents aged 45-65. The dependent variable is the average offspring percentiles rank. Children and Parent percentiles based on global earning distribution for each generation. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. Panel (a) 5-years average includes years with zero earnings. Panel (b) 5-years average includes only years with positive earnings. Coefficients are WLS estimates, over 131,895 observations. Controls: children's sex, parent's age and parent's sex. *Source:* Own elaboration based on social security records.

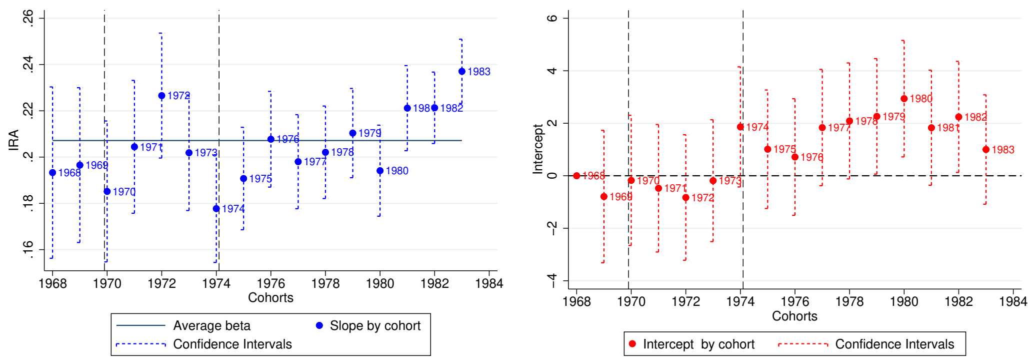


(a) Permanent income includes zeros



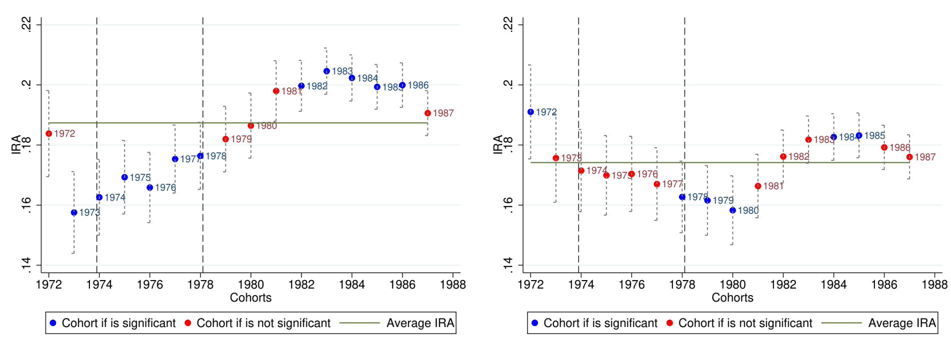
(b) Permanent income excludes zeros

FIGURA B.3 Intergenerational Ranking Association by cohorts. Own sample earning distribution (cohorts when child is aged 28 to 32). *Notes:* cohorts when child is aged 28 to 32, parents aged 45-65. The dependent variable is offspring's percentiles rank based on average earning. Children and Parent percentiles based on own sample earning distribution for each generation. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. Panel (a) 5-years average includes years with zero earnings. Panel (b) 5-years average includes only years with positive earnings. Coefficients are WLS estimates, over 131,895 observations. Controls: children's sex, parent's age and parent's sex. *Source:* Own elaboration based on social security records.



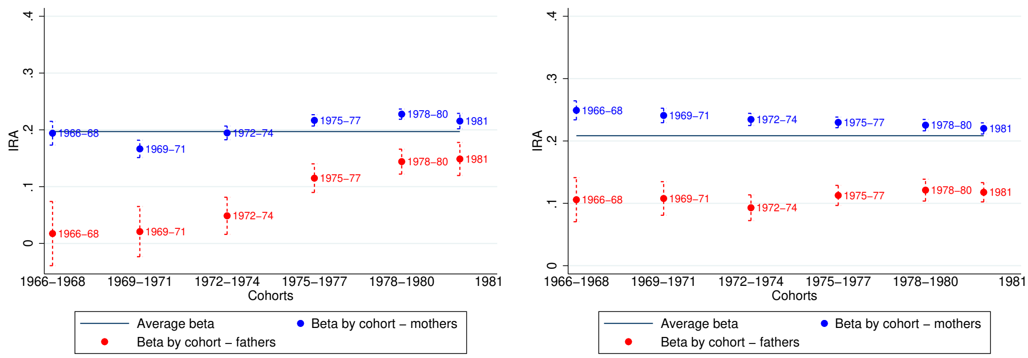
(a) Slopes (b) Intercepts

FIGURA B.4 Intergenerational Ranking Association by cohorts, multiple intercepts. Global earning distribution (cohorts when child is aged 28 to 32). *Notes:* The dependent variable is the average offspring percentiles rank. Children and Parent percentiles based on global earning distribution for each generation, 5-years average includes years with zero earning. Panel (a) 5-years average includes years with zero earning. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. Coefficients are WLS estimates, over 131,895 observations. Controls: children's sex, parent's age, and parent's sex. *Source:* Own elaboration based on social security records.



(a) Global earning distribution (b) Own sample earning distribution

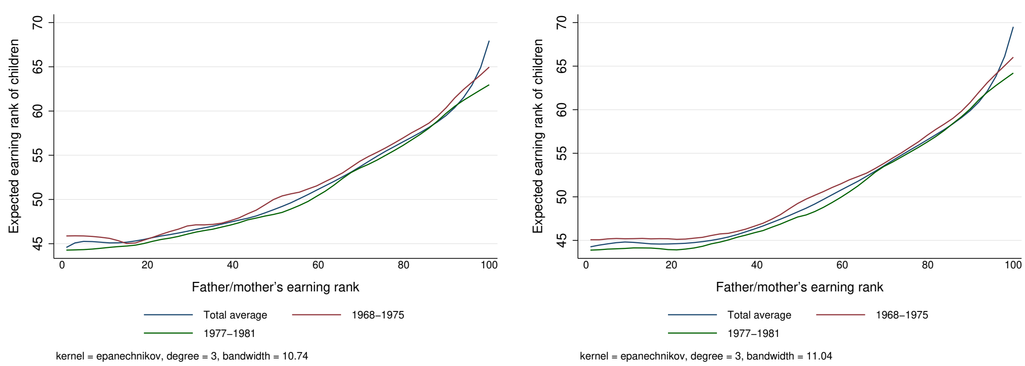
FIGURA B.5 Intergenerational Ranking Association by cohorts. Global and own earning distribution, 5 years average includes zeros (cohorts when child is aged 24 to 28). *Notes:* Cohorts when child is aged 24 to 28, parents aged 45-65. The dependent variable is offspring's percentiles rank based on average earning for own sample, and the average offspring percentiles rank for global sample. Children and Parent percentiles based on global earning distribution (Panel a) and own sample earning distribution (Panel b) for each generation. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. Coefficients are WLS estimates, over 204,121 observations. Controls: children's sex, parent's age and parent's sex. *Source:* Own elaboration based on social security records.



(a) Global earning distribution

(b) Own sample earning distribution

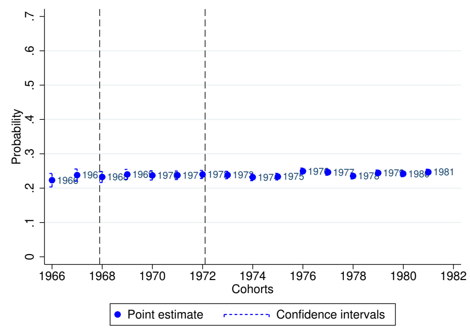
FIGURA B.6 Intergenerational Ranking Association by grouped cohorts when fathers and mothers are considered separately. 5 years average includes zeros. *Notes:* Cohorts when child is aged 30 to 34. The dependent variable is offspring's percentiles rank based on average earning for own sample, and the average offspring percentiles rank for global sample. The child cohorts are grouped in threes, leaving the last year (1981) as a group by itself. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. Panel (a) 5-years average includes years with zero earnings, using the global earning distribution. Panel (b) 5-years average includes years with zero earnings, using own sample earning distribution. Coefficients are WLS estimates, over 100,850 observations. Controls: children's sex, parent's age, and parent's sex. *Source:* Own elaboration based on social security records.



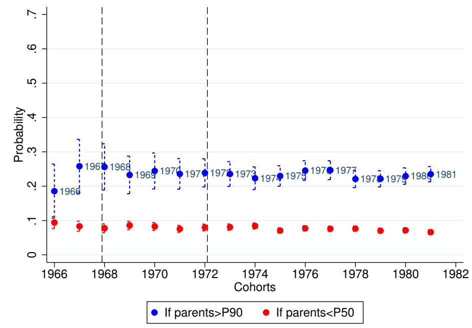
(a) Permanent income includes zeros

(b) Permanent income excludes zeros

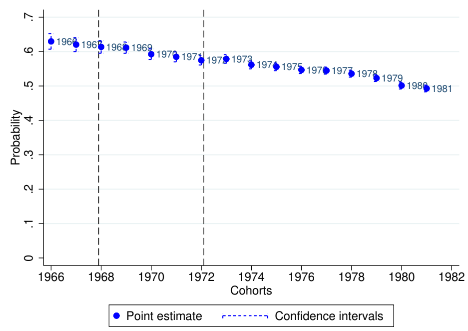
FIGURA B.7 Expected percentile of earning rank of sons based on parent's earning rank. 5 years average includes zeros, own sample earning distribution. *Notes:* Cohorts when child is aged 30 to 34. The dependent variable is offspring's percentiles rank based on average earning. Children and Parent percentiles based on global earning distribution for each generation. Estimates based on non-parametric methods, over 100,850 observations. *Source:* Own elaboration based on social security records.



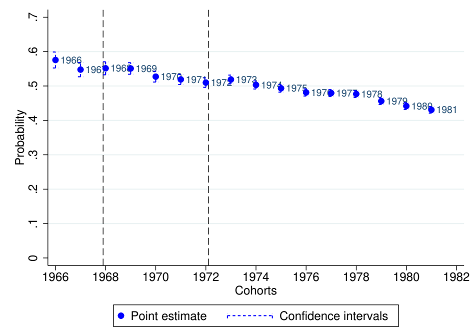
(a) Persistence (±10 percentiles than the parents)



(b) Directional Rank Mobility

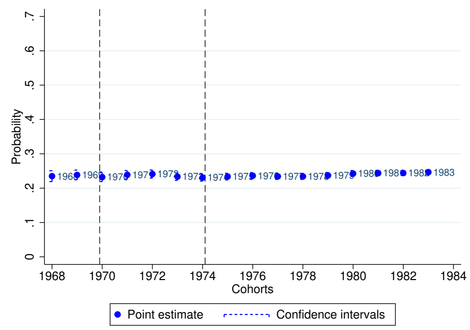


(c) Upward transition probability (+1 percentile)

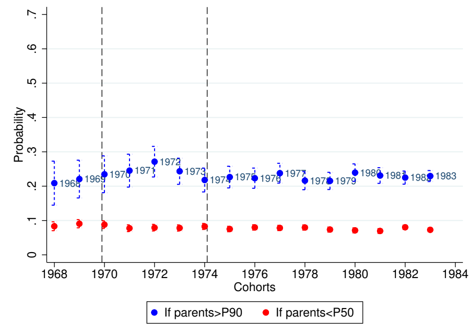


(d) Upward transition probability(+5 percentile)

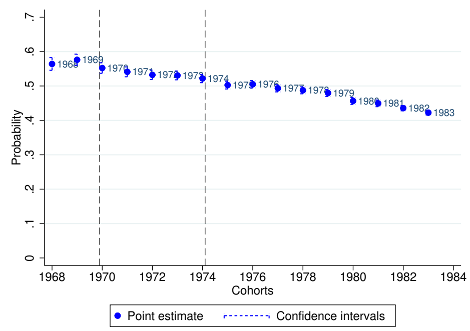
FIGURA B.8 Transitions for cohorts when child is aged 30 to 34. Own sample earning distribution. (5 years average includes zeros). *Notes:* Graph (a) represents the probability that the child belong to the same percentile than their parents or with a difference of +/- 10 percentile. Graph (b) represents the likelihood for an individual to surpass their parent's place in the distribution. Graph (c) represents the likelihood for an individual to surpass their parent's place in the distribution by a amount of 5. Graph (d) represents the probability that the child exceeded the 90 Percentile when the parents belong to the first half of the distribution of their generation, or when the parents belong to the top Decile of the distribution of their generation. Coefficients are OLS estimates, over 100,850 observations. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. *Source:* Own elaboration based on social security records.



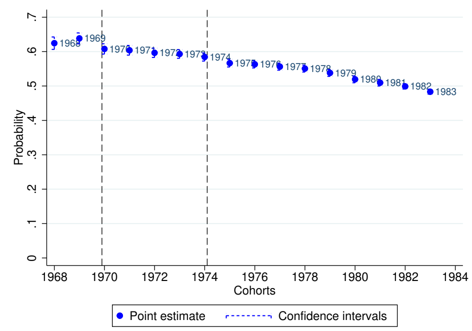
(a) Persistence (±10 percentiles than the parents)



(b) Directional Rank Mobility



(c) Upward transition probability(+5 percentile)



(d) Upward transition probability (+1 percentile)

FIGURA B.9 Transitions for cohorts when child is aged 28 to 32. Own sample earning distribution. (5 years average includes zeros). *Notes:* Graph (a) represents the probability that the child belong to the same percentile than their parents or with a difference of +/- 10 percentile. Graph (b) represents the likelihood for an individual to surpass their parent's place in the distribution. Graph (c) represents the likelihood for an individual to surpass their parent's place in the distribution by a amount of 5. Graph (d) represents the probability that the child exceeded the 90 Percentile when the parents belong to the first half of the distribution of their generation, or when the parents belong to the top Decile of the distribution of their generation. Coefficients are OLS estimates, over 131,895 observations. The dotted lines identify the cohorts whose permanent income was generated considering 2002 income. *Source:* Own elaboration based on social security records.

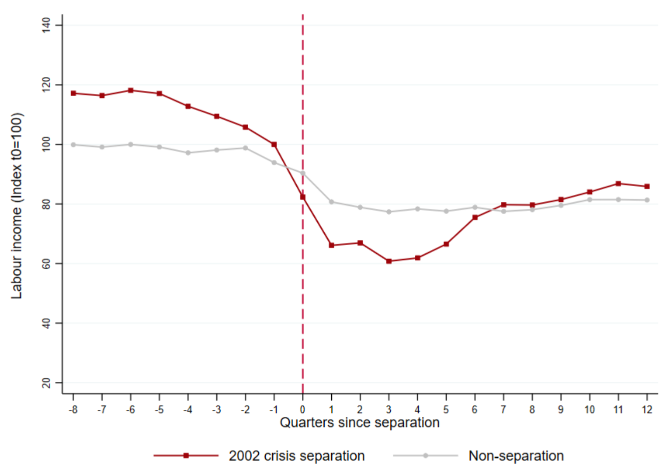


FIGURA B.10 Evolution of labor incomes before and after the unemployment event (treated vs control parents). *Notes:* The treatment group include the set of parents with unemployment event between june of 2002 and july of 2003. The control group is the set of parents without a separation in the period. *Source:* Own elaboration based on social security records.