I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13070

Was Falling Inequality in All Latin American Countries a Data-Driven Illusion? Income Distribution and Mobility Patterns in Uruguay 2009-2016

Gabriel Burdín
Mauricio De Rosa
Andrea Vigorito
Joan Vilá

MARCH 2020

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13070

Was Falling Inequality in All Latin American Countries a Data-Driven Illusion? Income Distribution and Mobility Patterns in Uruguay 2009-2016

Gabriel Burdín
University of Leeds, IZA and IECON, FCEA, Universidad de la República

Mauricio De Rosa
IECON, FCEA, Universidad de la República and Paris School of Economics

Andrea Vigorito
IECON, FCEA, Universidad de la República

Joan Vilá
IECON, FCEA, Universidad de la República

MARCH 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Was Falling Inequality in All Latin American Countries a Data-Driven Illusion? Income Distribution and Mobility Patterns in Uruguay 2009-2016*

To contribute to the debate on the recent inequality fall in Latin America, we provide evidence on the primary income distribution in Uruguay for 2009-2016 and assess mobility patterns. Comparing household surveys micro-data and a unique array of matched personal-firm income tax records, we find that trends are sensitive to the data source and inequality measure. Gini and Theil indices decreased, with a milder fall in tax records than in household surveys. Whereas in tax records synthetic indices fell within the bottom 99% offsetting increased concentration at the top, in household surveys the largest reduction occurred at the top. In turn, tax records estimates of top 1% income shares remained steady at around 15%, but decreased in household surveys throughout the whole period. Moreover, top income positions were stable, with average persistence rates at the top 1% close to 80%. Meanwhile, the equalizing effect of income mobility was very modest.

JEL Classification: D31, H24, O54

Keywords: top incomes, income inequality, mobility, personal income taxation, tax records, Uruguay

Corresponding author:
Gabriel Burdin
Leeds University Business School
Maurice Keyworth Building
LS2 9JT, Leeds
United Kingdom

E-mail: g.burdin@leeds.ac.uk

* We are grateful to Gustavo González, former coordinator of Asesoría Económica at Dirección General Impositiva, and to his staff, Fernando Peláez and Sol Mascarenhas, for the invaluable help and comments received during this research. Facundo Alvaredo, Verónica Amarante, Marisa Bucheli, Fernando Esponda, Juan Carlos Gómez Sabaini, Rosa Grosskoff, Juan Pablo Jiménez, Nora Lustig, Jorge Onrubia, Nelson Noya, Darío Rossignolo, Gabriela Pacheco, Alberto Sayagues and participants at Taller Desigualdad y Tributación a los Altos Ingresos (CEF-ECLAR AECID); Fiscal Policy and Income Redistribution in Latin America Workshop, CEQ, Tulane University; HLEG OECD Workshop (Berlin); ECINEQ and Instituto de Economia weekly seminar provided valuable comments and suggestions to previous versions of this paper. Centro de Estudios Fiscales (CEF) provided financial support to early versions of this research. All errors remain our own.

1 Introduction

In contrast to the remaining regions of the world, many studies attest that in the first fifteen years of this century, most Latin American countries experienced substantial reductions in monetary poverty and personal income inequality (Lustig et al., 2011; Cornia, 2014; Alvaredo and Gasparini, 2015). Whereas this decline was very fast in 2000-10, it continued at a slower pace in the subsequent five years and, in most cases, came to an end around 2015.[1] In spite of these recent improvements, income concentration in Latin America is still very high compared to most regions in the world (Alvaredo and Gasparini, 2015) and the interplay among economic growth and redistribution, as well as the paths and public policies needed to promote further redistribution and sustain present achievements are an open academic and public debate.

To date, most research on the recent inequality trends in Latin America has been based on household surveys information, which provides accurate income estimates for low, middle and upper middle income strata but might be subject to underreporting and undercoverage at the top of the distribution (Altimir, 1987; Székely and Hilgert, 1999; Cowell and Flachaire, 2015; Bourguignon, 2015; Lustig et al., 2019). In this vein, the findings of the tax-returns based top incomes research (Piketty, 2003; Atkinson et al., 2011) have reinvigorated the discussion on the validity of survey data to provide accurate inequality estimates. Moreover, evidence from personal income tax records for Argentina, Brazil, Chile and Colombia casts doubts on the magnitude of the recent inequality reduction and even over its trend (Alvaredo, 2010; Alvaredo and Londoño Velez, 2014; Flores et al., 2019; Morgan, 2017), suggesting that conclusions are very sensitive to the data source, inequality measure, unit of analysis and income definition considered.

Most analysts highlight three main reasons underlying the Latin American inequality fall (with ingredients varying depending on the country): i) a reverse to the mean after the 1980s and 1990s substantial inequality increase; ii) exceptional economic growth rates resulting from the commodity boom and an extremely favourable international context and; iii) a comprehensive package of redistributive reforms (Gasparini et al., 2018). In turn, a worsened international scenario and the lack of new policies aimed to reduce inequality can be associated to the post 2015 evolution. Thus, assessing whether the observed trends are robust to the data-set used in the analysis has relevant implications regarding the debate on whether economic growth led by the commodity boom and redistributive reforms improved economic and social well-being in the region.

However, reconciling the two strands of the literature to provide a consistent assessment of levels and trends observed in each data source requires accessing to micro-data from household surveys and tax records in order to carry out a careful harmonization process (Burkhauser et al., 2012). Because in many schemes tax units are individuals, top incomes studies are not able to reconstruct per capita household income, leaving aside homogamy, fertility differentials and other

[1] Tornarolli et al. (2018) identify further equalizing trends in 2014/15 for specific Latin American countries.

relevant features that affect household conformation and might amplify or mitigate primary income inequality. At the same time, in most cases, tax based administrative data lack of information from non taxable income sources, such as non contributory cash transfers and other public benefits. Hence, comparisons among household surveys and tax records based inequality measures are not straightforward.

At the same time, previous studies have not addressed the interplay between income equalization and persistence rates in the different points of the distribution or the role of income dynamics in improving short, medium and long term inequality in Latin American countries.[2]

To contribute to the current debate, this study provides evidence on the evolution of inequality among primary income receivers in Uruguay for 2009-2016. Drawing on the methodology proposed by Atkinson (2007), we compute top income shares estimates and synthetic inequality indices based on tax data and harmonized household surveys and present several robustness checks to support our main conclusions. At the same time, in order to explore the extent and depth of redistribution, we assess persistence along the income distribution, particularly focusing in top positions. According to previous studies, the period considered in this research combined a significant inequality decrease from 2008 to 2013 (per capita household income Gini index falling from 0.45 to 0.40), with stability thereafter (De Rosa et al., 2018). Thus, this investigation covers the period of apparently rapid decline in income concentration and its later slowdown.

This study is mainly based on a comprehensive administrative personal income tax micro-database (Impuesto a la Renta de las Personas Físicas -IRPF- and Impuesto a la Seguridad Social -IASS) matched to the corresponding firms' balance sheets submitted to the tax authorities (Dirección General Impositiva, DGI) in 2009-2016.[3] Since they include information from the social security records, these data cover the universe of formal workers (with earnings below or above the minimum tax threshold), capital income earners and pensioners, comprising around 75% of the adult population aged 20 and more. DGI personnel anonymized these data-sets for research purposes. At the same time, we used micro-data from official household surveys (Encuestas Continuas de Hogares, ECH) gathered by Instituto Nacional de Estadística (INE) to match the full adult population and carry out inequality comparisons.[4]

This paper contributes to the existing literature in three main avenues. First, we provide further evidence on the evolution of primary income inequality in Latin America among income receivers. Compared to previous studies available for the region, we provide one of the most comprehensive reconciliation exercises between household survey and tax data to date, analyzing

[2]Due to the lack of suitable data, most studies have been based on household survey pseudo panels or annual official household survey panels.

[3]Since personal income taxation in Uruguay was restored in 2007 (after a 33 years interruption), the availability of tax records for research purposes is very recent.

[4]Burdín et al. (2014a,b) and Burdín et al. (2015) provide a preliminary reconciliation of tax and household survey data on incomes and compute top income shares in Uruguay for a shorter period (2009-2011 and 2009-2012). In this research, we provide estimations for a larger time-span (2009-2016) and also improve significantly the information on capital income by exploiting for the first time matched employer-employee data.

the gaps between the two data-sources across the entire income distribution, but with a particular focus on top income groups. Our findings support the hypothesis that there was a decline in income concentration in Uruguay when assessed on the basis of synthetic indices, regardless the dataset. However, tax records based calculations show a milder decline than those from harmonized household surveys. Secondly, we show that tax data reveal that top income shares were stable and, furthermore, point estimates started to rise after the inequality reduction period finished. In sharp contrast, household survey based calculations exhibit a decline throughout the whole period. We also conclude that whereas tax records based calculations show an inequality fall of the bottom 99% offsetting increased concentration at the top throughout the whole period, In sharp contrast, household survey based calculations exhibit a decline throughout the whole period, the larger inequality reduction in household surveys occurred at the top. Thirdly, we exploit the panel structure of tax records to provide evidence on intra-generational top income mobility, adding to the recent yet scant literature on this topic. Our estimations clearly convey high persistence rates, with larger values for top fractiles. These results suggest that diminished inequality didnot imply a significant re-ranking among earners. In spite of this, we document that persistence rates were lower in the period of decreasing inequality. At the same time, we show that mobility has a very modest effect on inequality reduction, indicating that annual estimations depict an adequate description of the actual medium term income distribution.

The remainder of this paper is organized as follows. Section 2 reviews previous research on inequality and top incomes shares in Latin America and Uruguay. Section 3 describes the data sources and methods used in this study. Section 4 contains the main results and Section 5 concludes.

2 Inequality, top incomes shares and mobility patterns in Latin America

We first present a short overview of international studies assessing the accuracy of household surveys to capture the income sources of interest in this study, focusing on the discussion on top incomes shares estimations and income mobility (2.1). After that, we summarize the existing evidence on top incomes shares in Latin America (2.2) and the recent evolution of inequality in Uruguay (2.3).

2.1 Primary income distribution and top income shares

Considering the caveats of household surveys to capture income from top earners and the short time span they cover, distributional studies have recovered the tradition of analyzing income tax administrative records information (Feenberg and Poterba, 1993; Atkinson, 2007; Atkinson et al., 2011). Thus, the related literature on top incomes has been notably expanded over the last three lustrums (Piketty, 2003; Atkinson et al., 2011; Alvaredo et al., 2013). These studies show that synthetic inequality measures, such as the Gini index, have demonstrated to be sensitive to misreporting problems at the top of the income distribution, even if high income groups represent by definition a very small fraction of the population (Leigh, 2007; Alvaredo, 2011). Furthermore, the underepresentation of richer strata can lead to wrong evaluations of progressivity and redistribution effects of income taxation.[5]

As mentioned in the introduction, due to informational constraints, tax records based studies mainly assess inequality considering individuals and primary income. Depending on the tax regime and the definition of taxable income, in most cases this information does not allow to reconstruct households and to consider the whole set of income sources, which might be the relevant unit for many assessments and, particularly, for public policy design. At the same time, these data are subject to evasion, avoidance and behavioural responses to changes in tax rates. For instance, Feenberg and Poterba (1993) assess the participation of top income groups in the United States based on personal income tax information between 1951 and 1990, showing that the rise in top income shares was partly driven by a substantial reduction in top marginal tax rate from 70 to 28% implemented in 1986, that impacted evasion rates at the top.

Thus, a bulk of the literature has been trying to create harmonized series to carry out more accurate comparisons among data sources. For instance, Burkhauser et al. (2012) analyze inequality trends in household surveys and personal income tax data for the United States in 1967-2006, previously harmonizing the Current Population Survey to make it consistent with administrative data. They find that once income and tax units are consistently defined across data sources, differences are shortened, even though modifications in the tax system and survey design may explain differential trends in some periods. In order to overcome these caveats, the recent literature has been moving forward to provide a common ground by developing new methods that combine household survey and tax data to ensure that the upper tail is properly captured (Jenkins, 2015; Alvaredo et al., 2016; Piketty et al., 2017; Anand and Segal, 2017; Blanchet et al., 2018). However, to date, there is not a consensus on which is the "benchmark" distribution and there is an ongoing discussion on the appropriate correction methods.

Meanwhile, there are scarce studies assessing top income receivers mobility. The available ones conclude that persistence rates are higher at the upper tail of the distribution compared to the remaining strata (Aaberge et al., 2013; Auten et al., 2013; Kopczuk et al., 2007; Jenderny, 2016). At the same time, there is also limited evidence on the interplay among inequality and mobility. In the case of Norway, Aaberge et al. (2013) find that augmented top incomes mobility coexisted with increased shares at the top of the distribution.

[5] In spite of this, Leigh (2007) argues that the top 1% estimates are a good proxy of Gini indices rankings across countries.

2.2 The recent evolution of top income shares in Latin America

The first attempts to correct household survey income underreporting in Latin America can be traced to Altimir (1987)'s adjustment to national accounts that was included in Economic Commission for Latin America (ECLAC) inequality estimations. However, this methodology has shown to have many caveatsain (mainly coming from the quality and paucity of national accounts information) and recently ECLAC discontinued this procedure.

Despite the longstanding Latin American tradition in distributional studies, research focused on top income groups has been less frequent, partly due to scarce data availability, to the weaknesses of income taxation in the region and to the lack of relevant covariates in administrative data. To date, there is available evidence for Argentina (Alvaredo, 2010); Colombia (Alvaredo and Londoño Velez, 2014); Brazil (Souza and Medeiros, 2015; Morgan, 2017); Chile (López et al., 2013; Fairfield and Jorratt De Luis, 2016; Flores et al., 2019) and Uruguay (Burdín et al., 2014b; De Rosa and Vilá, 2017). However, many of these studies cover a shorter period than the top incomes scholarship for developed countries and either rely on tabulations for specific years or are based on micro-data that cover tax-payers or the upper income strata.

In regard to the period of recent decline, most top incomes studies conclude that inequality trends vary depending on the data source (Table 1). For instance, Alvaredo and Londoño Velez (2014) find that top income shares in Colombia remained steady (at around 20%) in the period that household survey-based Gini indices fell (2006-2010), even when corrected for underreporting. In turn, Flores et al. (2019) identify opposite trends for Chile, with an increase in tax based top incomes shares since 2000. Souza and Medeiros (2015) analyze the case of Brazil during 2006-2012 using the Blanchet et al. (2018) tax-based correction on household survey data. They report that inequality indices remained stable, with top income shares representing around 25% of total income throughout the whole period. However, the more striking results come from Morgan (2017), who analyzes a longer span combining household survey and tax information, following the Distributional National Accounts (DINA) guidelines (Alvaredo et al. (2016)). He finds a trend towards increased or steady income concentration in Brazil, contradicting most of the previous research based on household survey data, that unanimously identified a consistent and long period of rapid inequality decline (Lustig et al., 2011; Barros et al., 2006). However, the study also reports a decline in labour income inequality which is consistent with the previous literature and with the income sources mainly captured by household surveys. Since previous studies for Latin American countries were not able to exploit micro-data for a significant fraction of the population, the corresponding comparisons did not include tax records based synthetic inequality indices.

Even when tax records are available, identifying correctly capital income can be difficult due to the design of tax systems and particularly the interplay among firm and personal income taxation. For instance, in their study for Chile covering 2005-2009, Fairfield and Jorratt De Luis (2016) and Flores et al. (2019) use information from individuals and firms tax returns and im-

Table 1: Top income shares and Gini indices in Latin American countries. Circa 2000-2015

Country	Year	Top 1% share (primary income)	Source	Gini coefficient
Argentina	2001/06	14.3 / 16.8%	Alvaredo (2010)	0.504 / 0.493
Brazil	2001/15 2005/12	26.3/ 27.5% 22.7 / 26.4%	Morgan (2017) Souza and Medeiros (2015)	0.583 / 0.513 0.556 / 0.526
Chile	2000/15	20.2 / 23.7%	Flores et al. (2019)	0.526 / 0.448
Colombia	2007/10	20.7 / 20.4%	Alvaredo and Londoño Velez (2014)	0.59 / 0.554

Note. The sources for top income share's estimations (primary income) are Alvaredo (2010); Morgan (2017); Souza and Medeiros (2015); Flores et al. (2019); Alvaredo and Londoño Velez (2014). Non of the top income shares depicted were scaled up to National Income. Gini indices based on household surveys are available in SEDLAC (2019), and refer to per capita household income.

pute accrued profits and accumulated undistributed profits to taxpayers using ownership shares directly estimated from businesses tax-return forms. These studies indicate that although levels are extremely sensitive to this procedure, trends do not vary.

Finally, intra-generational mobility studies for Latin America are also scarce and mostly rely on pseudo -panels. In the context of the top incomes literature, only Cano (2015) was able to calculate persistence rate for the top fractions of the population.

2.3 Recent inequality trends in Uruguay

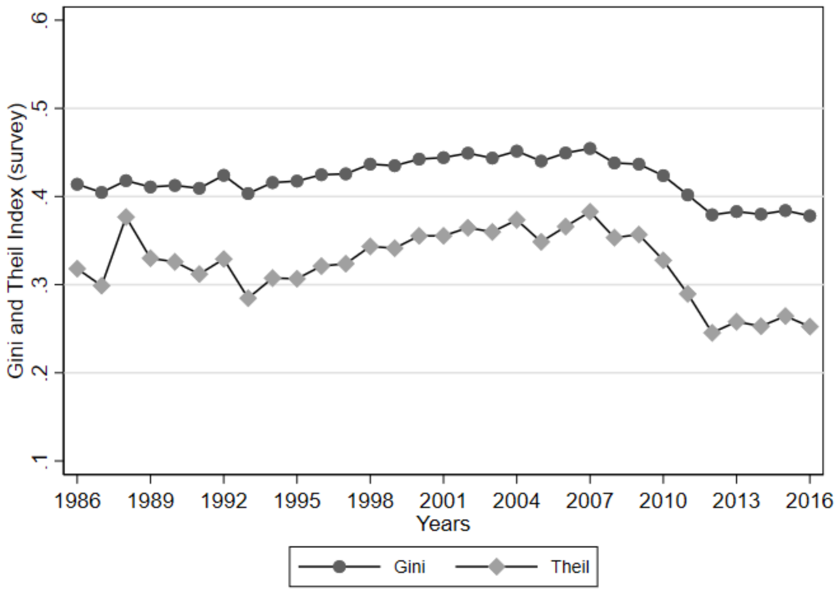
Uruguay is a low inequality country in the Latin American context. However, income concentration started to fall in 2008, after 15 years of stability or inequality increase, and later than most countries of the region (SEDLAC, 2019; ECLAC, 2019).[6] In this case, reduced inequality resulted from a combination of outstanding economic growth (led by the commodity boom) and employment rates coupled with a comprehensive package of redistributive reforms promoted after the centre-left coalition Frente Amplio took office in 2005 (see Figures 1 and A.1).

Although it is difficult to single out the specific effect of a particular intervention, most studies highlight the key role of increased minimum wages; the restoration of centralized wage-setting mechanisms; a tax reform including the reinception of personal income taxation in 2007

[6] In fact, household survey information reveals that the concentration trend that started in 1998 and peaked with the 2002 severe economic crisis still remained until 2008 (Amarante et al., 2014)

and; a significant expansion of non-contributory cash transfer schemes (Amarante et al., 2014).

Figure 1: Gini and Theil indices. Per capita household income, 1986-2016



Note. Own calculations based on ECH micro-data. Per-capita household income includes all cash and in-kind income sources and rental imputed income. For a complete description of the household survey, see Section 3.

3 Data and methodology

We first describe the main features of the data-bases used in this research (3.1.1) and then present the methods implemented to estimate top incomes shares and the remaining inequality measures (3.2). Finally, we turn to the assumptions and procedures underlying the mobility analysis (3.3).

3.1 Data

3.1.1 Income tax micro-data

The Uruguayan tax system is mainly based on indirect taxes, which roughly represent 65% of total fiscal revenue. Personal income tax was originally established in 1961 but, jointly with inheritance taxation, was abolished in 1974 by the de facto regime that ruled Uruguay during 1973-1985. Framed in an overarching tax reform, a new and more comprehensive personal income scheme was passed in 2006. The reform introduced a dual personal income tax (Impuesto a la Renta de las Personas Físicas, IRPF), combining a progressive tax schedule on labour income and pensions with a flat tax rate on capital income and a corporate income tax (Impuesto a la Renta de las

Actividades Económicas, IRAE).[7]

Details on tax rates for the three taxable income sources can be found in Tables A.1, A.2 and A.3. Although tax units are individuals, married couples can fill a joint labour income tax return. In practice, only 1.8% of the taxpayers choose this regime. Table A.4 depicts average income for different fractiles in Uruguayan pesos. In most brackets, a substantial increase in current and real incomes can be noticed. The tax schedule remained unchanged in 2009-2016, except for a relatively small tax increase for top income brackets in 2012.[8]

DGI created anonymized databases for research purposes that put together two administrative data sources: (a) the universe of IRPF and IASS tax payers for 2009-2016, which include in detail information on capital, pension, labour income for each occupation, tax burden and deductions (Table A.5); (b) the universe of labour income and pensions from social security records (provided by the Social Security Institute, Banco de Previsión Social, BPS) for formal workers and pensioners. As BPS acts as the retention agent for all individuals, the information on labour earnings and pensions included in the micro-data comprises pensioners and the universe of workers contributing to the social security, despite being net tax payers or not. Additionally, each record contains information on sex, age, industry, and whether the individual is a salaried worker or self-employed. Additionally, DGI provided a supplementary database with information on income and taxes of those personal services societies that chose to pay corporate income tax (IRAE) instead of IRPF (see row IRAE in Table A.5). This option is available for liberal professionals and, thus, these earnings can be assimilated either to mixed or labour income. The resulting micro-database covers 75% of the population aged 20 years and more.[9]

We grouped capital income in the following categories: profits and dividends; housing rents; interests from bank deposits and; other capital income. As most top incomes studies, we excluded capital gains. Due to the bank secrecy act and to previous regulations that allowed firms to issue bearer shares, we did not access to micro-data on interests and non nominative profits.

From Table A.6 it can be noticed that while the first is not a relevant concern, non nominative profits account for a half of total profits.[10] Since we lacked information on the characteristics of non nominative profits receivers, to assign the total amount among individuals in the tax-records micro-data, we distributed it proportionally to total capital income held by the corresponding

[7]Although pensions were originally included in IRPF, soon after the reform this component was declared unconstitutional. As a result, pensions were no longer taxed by IRPF; instead, a new progressive tax on pensions with similar characteristics was passed in July 2008, known as Impuesto de Asistencia a la Seguridad Social (IASS).

[8]Recent evidence suggests that this change did not result in a reduction of reported income after the reform, and, therefore, it did not affect top income shares estimations, although it may have had minor impact on income composition for some groups of taxpayers, (Bergolo et al., 2019).

[9]The remaining 25% is composed by informal workers (38,9%), unemployed (10,9%) and individuals out of the labour force not receiving pensions or capital income (50.2%).

[10]In recent years, to comply with the international regulations set by the Basel agreement, Uruguay restricted the issuance of bearer shares. In spite of this policy change, the percentage of non nominative profits looks steady in the period under analysis. Thus, potential trespassing from non nominative to nominative profits does not seem to be a relevant concern.

individual[11].

It is noteworthy that until 2016, firms were allowed to keep undistributed profits without any time limit. Thus, instead of declaring formal profit withdrawals (taxed at a 7% personal income rate additional to the 25% rate on corporate income), many firm owners took cash advances. Thus, our estimations convey a surprisingly low number of profit withdrawals per year (less than 10% of the firms distributed benefits) and this is partly explained by payments in advance representing a large proportion of distributed profits. Since these payments are singled out in the firms balance sheets data-base, we were able to partially reconstruct the actual distribution of capital income had these payments in advance been declared as distributed profits.

Corporate tax declarations and balances are available for the sub-set of firms with revenues above 40.000 U$S a month, that are obliged to present annual balances to DGI (around 60% of registered firms). For this subset, we were able to match individuals appearing in the tax records micro-data to the balances of the firms they are related to (either being employees or owners). In this way, it is possible to compute accrued, reinvested, undistributed and distributed profits for each firm and fiscal year.[12]

We first computed the amount of undistributed profits for each year. Secondly, based on the balance line indicating "share-holders/owners withdrawals in advance", we estimated the potentially undistributed profits and checked whether the firm also distributed profits during the same year or the next. If the firm had a positive value in the "potentially undistributed profits" line and in the next year profits were distributed and these accounts fell to zero, we only considered the actual distributed profits.

Since we lacked information allowing to identify business owners or share-holders and we could only label as such those individuals withdrawing profits, we assigned "potential profits withdrawals" amounts based on three different assumptions. In the first one, we distributed these additional profits among all the individuals we could identify as firm owners based on different years withdrawals. In those cases in which we did not have this information, we created new individuals. Secondly, we distributed profit withdrawals among top labour income earners in the corresponding firm. Third, we combined the two previous criteria and created additional individuals in case the firm reported workers and profit withdrawals in the time span considered in this study. The three criteria yield to the same results, so we stick to the last one. The final number of newly created individuals was between 0,09 and 0,11% depending on the year (see Table A.7).

As in the case of most top incomes research, besides the standard limitations of tax data, a relevant caveat of this study comes from the fact that in Uruguay, tax units are individuals and

[11]As shown by De Rosa et al. (2018), there are very few firms that distribute profits in Uruguay, to a relatively limited number of individuals. Therefore, imputing non nominative profits only to nominative profits receivers, is likely to overestimate the concentration of capital incomes. By distributing it proportional to total capital income, the capital income distribution remains unchanged.

[12]In Uruguay the fiscal year corresponds to the calendar year.

we cannot observe how their income is combined in households. Because they are not comprised in the taxable income definition, we are also not considering relevant income sources such as the value of owner-occupied housing and private and non-contributory public transfers.[13]

3.1.2 The Uruguayan household surveys

The National Statistical Office (INE) gathers household surveys (Encuestas Continuas de Hogares, ECH) since 1968. At present, ECHs are nationally representative and are carried out throughout the whole year. They collect information in detail on household composition, labour force status and outcomes, socioeconomic variables and personal income by source. Further methodological details can be found in INE (2019).[14]

After-tax labour income is gathered for each household member aged 14 years or more, including cash and in-kind payments for salaried workers, self-employed and business owner (separately recording the main occupation and the remaining ones). The reporting period corresponds to the month previous to the interview. The survey also gathers information on the contributory status of the labour force in each occupation.

Except for profit withdrawals by the self-employed and business owners, capital income is captured in the household questionnaire, which implies that each item is added up for the whole household and attributed to the household head. The questionnaire also gathers interests, dividends, rents, benefits and imputed value of owner occupied housing. Capital income sources are reported on an annual basis; only imputed value of owner occupied housing is gathered for the month previous to interview.

Transfer income is separately collected for each individual and origin (public/private, domestic/remittances), including pensions (retirement and survival), child allowances, unemployment insurance, accident compensation and other non contributory benefits.

As in the rest of the world, the accuracy of household surveys has been a longstanding discussion in Latin America (Altimir, 1987; Székely and Hilgert, 1999). In the same vein, during the 1990 decade, several studies analyzed the accuracy of ECH to capture household income by source compared to National Accounts and expenditure surveys (Groskoff, 1992; Mendive and Fuentes, 1996; Amarante and Carella, 1997). More recently, Amarante et al. (2007) find that ECH captures 39.7% and 23% of the total amount of housing rents and interests on bank deposits. Based on a subsample of households with children aged 0 to 3 that gathered ID numbers and was merged to tax records, Higgins et al. (2018) find the expected misreporting pattern: overreporting in ECH below the median and underreporting thereafter. At the top 1% ECH captures 56% of

[13]Many studies indicate that both factors are relevant in Latin America, but with a greater role of the latter to explain the recent reduction of inequality (Lustig et al., 2011; Cornia, 2014; Alvaredo and Gasparini, 2015). Moreover, in the case of Uruguay, household survey based studies conclude that the static contribution of child benefits and other cash transfers is similar to the equalizing effect of the income tax (Bucheli et al., 2013; Amarante et al., 2014).

[14]Sample size was 46,550 households and 120,781 individuals in 2009 and 46,669 households and 128,204 in 2016.

DGI income.

In order to harmonize ECH information with income tax micro-data, we computed income for formal workers, pensioners and capital earners on an individual basis and restricted income sources to the ones captured by DGI micro-data according to the taxable income definition (see Burdín et al. (2014b) for details).[15]

3.2 Top income shares estimation: population and income controls

In order to estimate top income shares, we first computed income and population control totals following the methodology developed by Atkinson (2007). Although the standard practice in most top income studies is departing from National Accounts System (NAS) information (Atkinson, 2007; Atkinson et al., 2011), in Uruguay the last official estimation of the households income account is available for 1997. Thus, to estimate the income control we compute total income captured in tax records and add up an estimation of informal earnings by restricting ECH micro-data to individuals aged 20 or more (more on this below) that were not contributing to the social security and were not receiving pensions or capital income.[16] Tax records income represents around 50% of annual GDP, whereas ECH informal earnings account for 3% (Table 2). As a whole, the participation of the aggregate income control grows throughout the whole period. However, it is worth noticing that it never reaches 70%, which is the standard figure found in top incomes studies for developed countries.

In turn, computing the population control requires the definition of a reference population, since tax micro-data represent formal workers, capital income earners and pensioners. The standard practice in top incomes research is to consider the population projections of individuals aged 15 or 20 years and more. Since most top incomes studies for Latin America consider the latter, we stick to this criterion, as long as the number of individuals in DGI micro-data under that age is really low.

As a whole, Uruguayan tax records account for around 75% of the population aged 20 or more (Table 3).[17] As mentioned in the previous paragraphs, to account for total income, we added the sub-set of ECH individuals aged 20 or more with zero or informal earnings to DGI micro-data.

[15]Besides expanding the series with five additional years, with respect to Burdín et al. (2014b), we introduced several methodological modifications in the estimations and our final results differ. The two main innovations in this study rely in the of use a different method to include non nominative profits and interests and in using the matched employer-employee/owner data-base to identify undistributed profits that remained in firms.

[16]Burdín et al. (2014b) compared the procedure used in this study to the variant that starts from NAS, reconstructing the households income account based on several assumptions. Since the two options yielded to very similar results, we stick to the first method.

[17]One of the facts explaining the broad coverage of the adult population of the data base used in this study derives from the fact that informality rates in Uruguay are lower than in most Latin American countries. Since 2006, there was also an explicit policy promoting formalization: whereas in 2009 social security coverage rates were 67.8% of total workers and 80.6% among salaried workers, in 2016 these figures rose to 74.7% and 87.9% respectively. Although in Uruguay there is a family tax return option available, 98.5% of the individuals in our data-base choose the individual regime.

As it can be noticed by adding the second and fourth columns of Table 3, this value is above the total population (first column). Thus, we compressed the ECH population weight to fit the Population Projections using the factors displayed in the last column. This procedure presents a caveat since it assumes that individuals cannot simultaneously receive formal and informal income. The findings by Higgins et al. (2018) suggest that a significant fraction of low income population combine the two types of income. Though, we might be overweighting the lower tail of DGI.

Table 2: Income control

	2009	2010	2011	2012	2013	2014	2015	2016
Tax records	13,613	17,486	21,205	23,841	27,474	28,227	26,932	27,775
ECH	1,009	1,297	1,478	1,470	1,497	1,304	1,267	1,296
Total	14,623	18,783	22,684	25,311	28,971	29,531	28,199	29,071
GDP	31,661	40,284	47,962	51,265	57,531	57,235	53,274	52,687
Tax records/GDP	43.0%	43.4%	44.2%	46.5%	47.8%	49.3%	50.6%	52.7%
ECH/GDP	3.2%	3.2%	3.1%	2.9%	2.6%	2.3%	2.4%	2.5%
Total/GDP	46.2%	46.6%	47.3%	49.4%	50.4%	51.6%	52.9%	55.2%

Note. Own calculation based on tax records (DGI), household surveys (ECH) and GDP from Uruguay's National Accounts. GDP in millions of Uruguayan pesos (current). 1 U$S was equivalent to 20-23 Uruguayan pesos in the reference period.

Table 3: Population control

	Total population	Tax records	Tax record (%)	Survey population	Tax record + survey	Survey adjust (%)
2009	2,348,300	1,721,207	73.3	760,720	2,481,927	82.4
2010	2,370,788	1,722,902	72.7	743,279	2,466,181	87.2
2011	2,390,888	1,758,779	73.6	697,776	2,456,555	90.6
2012	2,410,258	1,793,012	74.4	687,845	2,480,857	89.7
2013	2,430,379	1,852,341	76.2	686,487	2,538,828	84.2
2014	2,451,739	1,928,833	78.7	676,524	2,605,357	77.3
2015	2,474,284	1,916,230	77.4	692,600	2,608,830	80.6
2016	2,497,361	1,923,850	77.0	710,096	2,633,946	80.8

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE). Second and third columns depict total number of adults in the tax records, both in absolute terms and as percentage of total adult population. Fourth and fifth columns depict informal and zero-income adult population in the survey and added to the tax data. The last column shows the adjustment to the survey data necessary to match the total control population.

Based on DGI micro-data, population and income controls on one side and harmonized ECHs on the other, we computed pre and post tax top income shares, synthetic inequality indices (Gini and Theil) and the corresponding group and income source decompositions (Shorrocks, 1981, 1999; Lerman and Yitzhaki, 1985). Confidence intervals were calculated by boostrapping (100 repetitions).

3.3 Mobility analysis

We exploited the longitudinal nature of DGI data to analyze persistence in individual positions along the income distribution, particularly focusing on top income holders. To implement this analysis we restricted the data-base to the balanced panel.

We first estimated average absolute and positional persistence rates. Both estimates arise from the following regression:

$$y_{t,i} = \alpha + \beta y_{t-x,i} + \epsilon_i$$

In the estimates of absolute persistence, y_{ti} corresponds to the final logarithm of total income and y_{t-xi} represents the same variable x years before. In the base estimates, the years considered are 2016 against 2009. In the case of positional mobility, a similar procedure is carried out but y_{ti} and y_{t-xi} represents the final and initial rankings. These exercises were also performed splitting the data by sub-period and gender.

In order to assess positional mobility we also built transition matrices, since this conventional and intuitive method allows to observe individuals' movements across different positions in the income distribution between two time points. Following Fields and Ok (1999), the transition matrix induced by transformation $x \to y$ is defined as the matrix $P(x,y) = [p_{rs}(x,y)] \in R_+^{mxm}$, where m are the specified income groups and p is the fraction of individuals belonging to class r in the distribution x and experiencing a transition to class s. By construction, $\sum_{s=1}^{m} p_{rs}(x,y) = 1$ for all r.

Finally, we assessed the distributional effect of income mobility by computing top income shares and inequality measures based on annual income and each individuals longitudinally-averaged income. The difference between these two measures is usually interpreted as the re-distributive effect of income mobility on long run income (Shorrocks, 1978, 1981).

4 Results

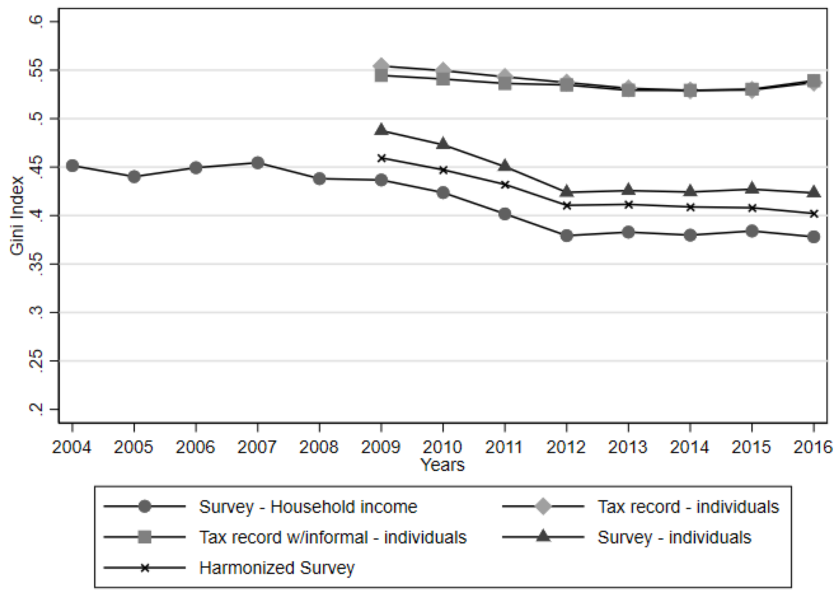
We first analyze the evolution of income inequality in Uruguay, assessing synthetic indices and top income shares trends. After that, we exploit the longitudinal nature of DGI data and study the persistence rates of individuals in their original positions across the income distribution.

4.1 The recent evolution of income inequality and top income shares in Uruguay

4.1.1 Synthetic inequality indices

Figure 2 depicts synthetic Gini indices computed on the basis of different ECH and DGI micro-data income aggregates. The longest line is ECH per capita household income, which corresponds to the variable used in most inequality studies. Its evolution indicates a sharp decline between 2008 and 2013 and stability thereafter. Although at higher levels, inequality among income receivers in ECH mimics the path of household income distribution, either considering original or harmonized data. In the three options, comparing 2009 to 2013 and 2016 yields to statistically significant differences.[18]

Figure 2: Gini index by income definition and source, 2004-2016



Note. Own elaboration based on household surveys (ECH) and tax records (DGI). In ascending order, the different income aggregates depicted include: (1) ECH per capita household income; (2) harmonized ECH (only formal income receivers, pre-tax earnings) and (3) ECH-formal and informal income receivers; (4) DGI income adding (weighted) ECH informal workers; (5) DGI income.

In turn, DGI micro-data based calculations are presented in two options. In the first case we consider the original information from the tax-records database and in the second one we depict the control income variable (by adding reweighted informal workers and non earners micro-data from ECH). The two lines exhibit a mild decline, with inequality indices converging since 2012 and slightly increasing by 2016. Again, 2009/2016 and 2009/2013 differences are statistically

[18] See confidence intervals in Table A.8.

significant.[19]

Thus, the five income variables confirm an equalising trend comparing 2009 to 2016 and throughout 2009-2013, indicating that these two findings are robust to the data base and harmonization criteria, even when levels are considerably higher in DGI data and the slope of the decline is significantly smaller. Table A.9 suggests that synthetic indices that weight differently the varied points of the income distribution also show a consistent reduction pattern, despite the data-source. Considering the whole period under study, ECH depicts a 25% inequality reduction, that rises to 42% for 2009-2013. Since decreasing rates were milder in DGI, the gap among the two sources widened in the last years. Meanwhile, discrepancies arise in the last period (2013-2016). Whereas household surveys estimations still indicate a slight decline in 2013-16, differences are not statistically significant in tax records data.

4.1.2 Top incomes shares

The three panels in Figure 3 depict the evolution of the top 10, 1 and 0.1% income shares. Although the point evolution of the top 10% is very similar to the path described by inequality indices previously presented, confidence intervals rule out the decline hypothesis, indicating stability throughout the whole period. Meanwhile, the top 0.1 and 1% clearly remained almost unchanged in 2009-2013 and exhibit an increase since 2014, although not statistically significant either.

Meanwhile, the shares of the bottom and middle income strata present a mild increase (Table 4). Notice that the top 1% holds a larger proportion of total income than the bottom 50% and this gap increased throughout the whole period. A similar comment applies to the middle 40% respect to the top 10%, but in this case the gap narrowed.

Table 4: Pre-tax income shares, 2009-2016

Inc. groups	2009	2010	2011	2012	2013	2014	2015	2016
Top 0.1%	5,0%	5,1%	5,5%	5,3%	5,6%	5,3%	5,9%	6,4%
Top 1%	14,7%	14,7%	15,1%	14,8%	14,8%	14,6%	15,3%	16,2%
Top 10%	47,5%	47,2%	46,6%	46,5%	45,8%	45,6%	45,8%	46,6%
Middle 40%	42,5%	42,6%	42,9%	43,0%	43,6%	43,8%	43,4%	42,9%
Bottom 50%	10,0%	10,2%	10,5%	10,5%	10,6%	10,7%	10,8%	10,5%

Note. Own elaboration based on tax records (DGI).

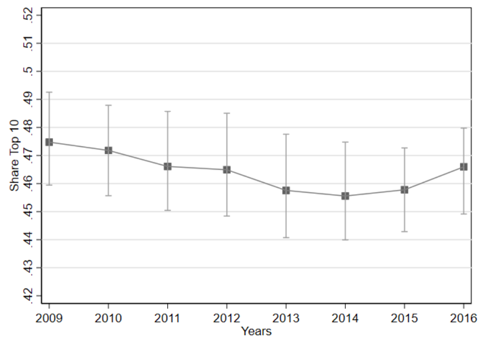
Considering the whole period, the point estimate of the top 1% share moved from 14.5 to 16%. These values place Uruguay among the countries with the highest concentration at the top in the World Inequality Database, being below the remaining Latin American countries, South

[19] These results also hold when considering only the original DGI data with no further imputations on undistributed and non nominative profits.

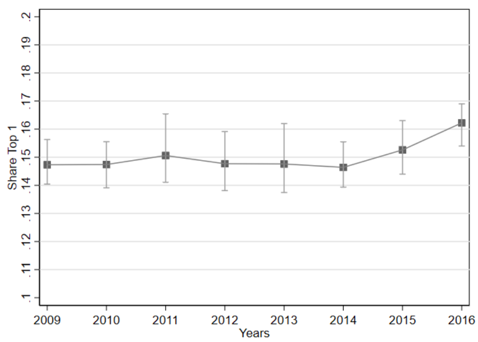
Africa and the United States (WID, 2019). It is noteworthy pointing out that this result is partly driven by the bias towards developed countries of WID, resulting from the lack of availability of tax records information at developing countries.[20]

Figure 3: Top income shares, 2009-2016

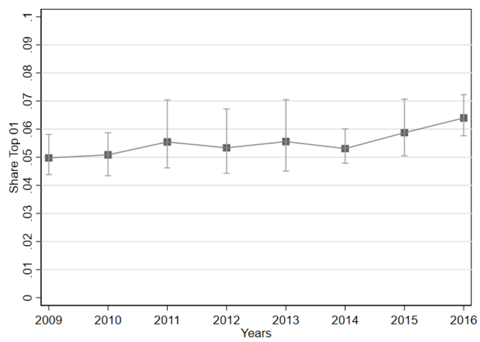
(a) Top 10%



(b) Top 1%



(c) Top 0.1%



Note. Own calculations based on tax records (DGI) and household surveys (ECH). See point estimates in Table 4.

4.1.3 Reconciling synthetic indices and top income shares

The increase in top incomes shares depicted by DGI data was relatively small and it is not statistically significant. However, one striking feature of Table 5 relies in the comparative evolution of the 1% share in the two data sources. Whereas in 2009 the DGI/ECH ratio was 85%, it fell to 55% in 2016. Thus, differently to synthetic indices, in this case results are sensitive to the data source.

The ECH/DGI ratios of the lower thresholds and average income for the top 10% and 1% shares suggest that the erosion of ECH took place at the higher strata. In fact, the 10% threshold is very similar in the two data sources, with almost constant ratios above 90% in the whole period.

[20] These results also hold when considering only the original data with no further adjustments imputing bank deposits, non nominative and undistributed profits.

However, in the case of the top 1%, this ratio falls from almost 90 to 74%. As expected, this loss in ECH‘s capacity to reach the higher strata increases with income (as highlighted in the comparison between the means ECH/DGI ratios for the two fractiles).[21]

Table 5: Top shares comparison by data source, 2009-2016

	Top 1% share		Top 1% Survey/Tax records		Top 10% Survey/Tax records	
Year	Tax records	Harmonized survey	Threshold	Mean	Threshold	Mean
2009	14.7%	11.5%	88.2%	74.7%	93.6%	86.2%
2010	14.7%	10.6%	83.7%	65.4%	89.6%	80.1%
2011	15.1%	9.5%	79.0%	56.5%	91.8%	76.8%
2012	14.8%	7.7%	68.8%	45.3%	90.4%	69.6%
2013	14.8%	8.5%	74.2%	49.9%	90.0%	72.5%
2014	14.6%	8.4%	74.8%	49.9%	89.3%	72.2%
2015	15.3%	8.7%	77.2%	51.5%	93.7%	75.0%
2016	16.2%	8.4%	73.9%	45.2%	90.7%	70.0%

Note. Own calculations based on tax records (DGI) and household surveys (ECH). The first block depicts top 1%'s share in the tax records and harmonized survey.

To dig into the conflicting trends depicted by top income shares vis a vis synthetic indices in DGI data, we carried out two group decompositions considering the following income categories: bottom 50%; middle (50-90%); middle-top (90-99%) and top (99-100%), and bottom 99% versus top 1% (Tables A.10 and 6). Although the aforementioned tables depict pre-tax income decompositions, the results and comments presented under this heading also hold for post-tax income based inequality indices in the two data-sources.[22]

The between group inequality fraction remained steady throughout the years in the Gini and Theil indices decompositions at DGI data. However, the last rows of the top panel clearly convey a remarkable contrast: whereas inequality decreased in the 3 poorer groups (with 2013 to 2009 ratios being 95.7, 90.4 and 97.2% respectively), a sharp increase was going on at the top throughout the whole period (2013/09 ratio=1.13%).[23] However, carrying out the same decomposition with harmonized ECH micro-data (bottom panel), yields to falling between group inequality. Recall that, at the same time, Gini and Theil indices fell monotonically in the four groups, with a larger reduction at the top 1% (the 2016 to 2013 ratio is 92.4, 92.1, 86.3 and 67.0% respectively).

[21] Assessing the reasons under this impoverishment in ECHs ability to capture the richest strata and the consequent decline in the ratios examined in the previous paragraph, is beyond the scope of this study. However, some conjectures can be raised considering that this occurred in a period of rapid income growth coupled with increased residential segregation (Rodríguez Vivas, 2019), and underreporting and refusal rates might have increased. On the side of DGI data, two main features might create an artificial inequality increase: reduced informality with the subsequent entries of low salaried workers in the data-base and a higher ability of the tax authority to enforce tax-payers.

[22] Due to space constraints, additional tables are not included in this document but they are available upon request to the authors.

[23] These results also hold when considering only the original data with no further adjustments imputing bank deposits, non nominative and undistributed profits.

Table 6: Inequality decomposition between two income groups, 2009-2016.

	2009	2010	2011	2012	2013	2014	2015	2016
			Tax records (DGI)					
Gini index	0,574	0,570	0,565	0,561	0,554	0,552	0,552	0,560
Between	0,125	0,125	0,129	0,126	0,126	0,125	0,131	0,141
Within	0,449	0,445	0,435	0,435	0,427	0,427	0,421	0,419
Overlap	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Between (%)	21,8	21,9	22,9	22,4	22,8	22,7	23,8	25,2
Within (%)	78,2	78,1	77,1	77,6	77,2	77,3	76,2	74,8
Overlap (%)	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Bottom 99%	0,524	0,519	0,510	0,508	0,499	0,498	0,494	0,497
Top 1%	0,355	0,364	0,390	0,383	0,400	0,385	0,408	0,423
			Harmonized survey (ECH)					
Gini index	0,581	0,569	0,561	0,544	0,547	0,541	0,555	0,551
Between	0,105	0,096	0,085	0,067	0,075	0,074	0,077	0,074
Within	0,476	0,473	0,476	0,477	0,472	0,467	0,478	0,476
Overlap	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Between (%)	18,0	16,8	15,2	12,4	13,7	13,7	13,8	13,5
Within (%)	82,0	83,2	84,8	87,6	86,3	86,3	86,2	86,5
Overlap (%)	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Bottom 99%	0,543	0,534	0,531	0,522	0,521	0,515	0,529	0,525
Top 1%	0,254	0,227	0,202	0,136	0,172	0,173	0,191	0,180

Note. Own calculations based on tax records (DGI) and household surveys (ECH). The table is divided in two panels, depicting tax records and harmonized surveys respectively. By construction, both micro-data bases refer to the same individuals and same incomes (pre-tax and formal total personal incomes). In each panel, Gini index is decomposed in *between* and *within* components, among the groups defined (bottom 99% and top 1%). Within group inequality is depicted in the last two rows of each panel.

In the second variant (Table 6) we collapsed the first three groups into one category. In this case, the "explanatory power" of between groups inequality also grew at DGI micro-data, highlighting the increased distance in the two groups average income. At the same time, this exercise yields, again, a sharp contrast between the 2009-2016 decreasing inequality trend of the bottom 99% (6% fall) and the opposite movement at the top 1% (20% increase). Similar results are obtained from the Theil index decomposition. Again, this result diverges from the findings at ECH micro-data (bottom panel) where, as in the case of the first exercise, both the between groups proportion and intra group inequality fell.

Thus, decreasing inequality at the bottom 99% (jointly considered or split into 3 groups) coupled with increased concentration at the top 1% is consistent with trends observed in ECH and its apparently reduced capacity to reach the rich. This finding is mirrored by the falling ECH/DGI average income ratio at the top 1% presented in 4.1.2. Whereas inequality reduction in harmonized ECH was led by the 90-99% and top 1% groups, the opposite happened in DGI, with equalisation mainly occurring at the bottom 50 and 50-90% groups.

The mild inequality reduction observed in DGI data reflects an offsetting fall at the bottom 99% against an increasing concentration at the top, that results in increased or stable shares. At the same time, at ECH inequality reduction is also fed by a better distribution in all groups (with larger reductions at the top). The latter can result either from richer households increased refusal rates or underreporting.

To conclude this subsection, three comments are noteworthy. First of all, the evolution of inequality at the bottom 50% rules out the possibility of DGI trends being driven by the formalization process. Secondly, and more important, the evolution of inequality at the top 1% is consistent with the observed divergence in DGI versus ECH share of this group. Thirdly, DGI figures suggest that the bottom 99% group inequality fall took was coupled with augmented inequality at the top led by this groups increased earnings.

4.2 The composition of income

The last subsection findings indicate that, in regard to inequality trends, the main difference among DGI and ECH data based estimations refers to inequality and average income at the top of the income distribution. Thus, the ability of ECH and DGI data to capture the different income sources can contribute to shed light on these discrepancies, particularly regarding capital income. To further explore this point, we analyzed the four income sources described in Section 3.1.1: labour, pensions, mixed income (i.e., liberal professionals earnings) and capital income (separately considering property rents, bank deposits, entrepreneurial profits and other items).

The findings presented in the previous paragraphs closely relate to the source composition of the different population groups. In fact, Table A.11 and Table A.12 depict the relative participation at DGI and ECH data of the four income groups previously considered, uncovering the expected pattern: labour income accounts for around 75% of total income at ECH, falling to 66% in DGI data. Since pensions share is similar in the two data-sources, the difference is entirely explained by capital income share which is around three and four times larger at the tax records database and grows throughout the period, whereas it falls in household survey data. Again, this pattern is consistent with the different trends in the evolution of top incomes shares observed in the two data-sets.

Inspecting the income source composition in DGI data, it can be noticed that, at the bottom 99%, the largest share corresponds to labour earnings and pensions, with a slight but increasing participation of mixed and capital income. Meanwhile, in 2016 the latter two sources equalize the labour earnings share at the top 1% and surpass it at the top 0.1%.[24] In regard to capital income, profits are clearly the most unequally distributed source. Whereas property rents are more relevant for centiles 90-99, profits account at the top for around 45% of capital income. This

[24]Due to the number of cases these estimations cannot be carried out at ECH micro-data.

predominance of both capital income and profits at the richest strata has been highlighted by the top incomes literature as a distinctive feature of developing countries, since in the developed world, executives compensations and high salaried workers have a larger participation (Alvaredo and Londoño Velez, 2014).

At the same time, it is worth pointing out the capital incomes share substantial increase at the top of the distribution throughout the whole period. As a matter of fact, our estimations also indicate that whereas in harmonized ECH the top 1% receives 37% of total capital income, this figure rises to 62% in DGI micro-data.

Tables 7 and A.12 depict the results of the Lerman and Yitzhaki (1985) Gini index income source decomposition based on DGI and ECH micro-data respectively. As expected, capital income is the most unequally distributed income source (with a Gini index very close to 1), followed by pensions (probably related to the number of individuals not being pensioners). R values clearly show that, in spite of its tiny share, capital income is largely correlated to total income. However, the decomposition yields to different patterns in the two data sources, with a larger share of labour income in ECH data. Conversely, the contribution of capital income and pensions is substantially larger in DGI, with an increasing share in the latter case. Finally, the negative sign of the marginal contribution of pensions to inequality indicates their equalizing effect, which is higher in ECH than in DGI. Labour and capital income exhibit a positive contribution in the two data sources, with the expected order and trend.

In line with previous studies on wage differentials, when opening the income distribution by source and gender, our estimations show that the participation of women in total and labour income decreases with the quantile (Figure 4, panel a), ranging from more than 50% below the median to 25% at the highest percentile. Estimations by Atkinson et al. (2018) for eight high income countries reach similar results. The presence of women is larger among pensioners, probably due to life expectancy patterns, but it reflects the same declining shape with shortened differences (60% and 40% respectively). Conversely, the presence of women is scarcer among mixed and capital income receivers. Considering the distribution of income instead of the number of earners (panel b) results are very similar, although in most cases women's share is even lower, probably reflecting their relative disadvantage within these categories.

4.3 The role of taxation

In this section, we briefly assess the progressivity and redistributive effects of personal income taxation in both household surveys and tax data (Table 8). Kakwani indices indicate that personal income taxation is progressive in the two data sources. However, levels are almost 20% higher in ECH, although in 2016 the two indices are very similar. This convergence results from the fact that tax progressivity at DGI shows a smooth decreasing trend throughout the whole period (13% fall in 2009-2016), whereas ECH values were almost steady and plummeted at the end.

Table 7: Inequality decomposition by income source. 2009, 2013 and 2016. (DGI Pre-tax income)

		2009	2010	2011	2012	2013	2014	2015	2016
Sk	Labor inc.	0,693	0,694	0,711	0,682	0,684	0,683	0,674	0,677
	Pensions	0,228	0,230	0,202	0,225	0,222	0,218	0,222	0,218
	Capital inc.	0,068	0,065	0,075	0,082	0,083	0,088	0,093	0,095
	Mixed inc.	0,011	0,011	0,011	0,011	0,011	0,011	0,010	0,010
Gk	Labor inc.	0,707	0,707	0,689	0,696	0,684	0,680	0,678	0,685
	Pensions	0,818	0,811	0,821	0,809	0,812	0,812	0,811	0,809
	Capital inc.	0,989	0,989	0,991	0,984	0,985	0,986	0,990	0,990
	Mixed inc.	0,999	0,999	0,999	0,999	0,999	0,999	0,999	0,999
Rk	Labor inc.	0,859	0,861	0,869	0,852	0,851	0,850	0,845	0,845
	Pensions	0,446	0,430	0,370	0,412	0,401	0,391	0,395	0,395
	Capital inc.	0,890	0,882	0,893	0,893	0,892	0,897	0,904	0,904
	Mixed inc.	0,968	0,968	0,969	0,960	0,960	0,960	0,960	0,960
Share	Labor inc.	0,732	0,741	0,754	0,720	0,719	0,715	0,701	0,708
	Pensions	0,145	0,141	0,109	0,133	0,130	0,125	0,129	0,122
	Capital inc.	0,105	0,099	0,117	0,128	0,132	0,141	0,152	0,152
	Mixed inc.	0,011	0,011	0,011	0,011	0,011	0,011	0,010	0,010
Change (%)	Labor inc.	0,039	0,047	0,043	0,038	0,035	0,032	0,027	0,032
	Pensions	-0,083	-0,089	-0,094	-0,092	-0,091	-0,093	-0,093	-0,096
	Capital inc.	0,036	0,034	0,043	0,046	0,049	0,053	0,058	0,057
	Mixed inc.	0,008	0,008	0,008	0,008	0,008	0,008	0,008	0,008

Note. Own elaboration based on tax records (DGI). Gini index income source decomposition (Lerman and Yitzhaki (1985)) is depicted. k is income source, S is the income share, G is the within source Gini index, R reports the correlation among each income source and total Gini, *share* represents the contribution of each source to overall inequality and *change* is the marginal effect of a 1% increase.

Figure 4: Proportion of female earners and women's income share by source and income fractile.

(a) Percentage of women

(b) Women's income share

Note. Own calculation based on tax records (DGI). The percentage of female earners and their income share (by income source and fractile), are depicted in panels (a) and (b) respectively.

Meanwhile, the comparison of before and after tax Gini indices (Reynolds-Smolensky coefficient), indicates a constant redistributive capacity of 2 percent points in the two data sources. Thus, the proportional redistributive effect in ECH is considerably higher than in DGI. However, Theil index presents a similar reduction in proportional terms in the two data sources (Table A.9).

It is worth noting that although personal income taxation is progressive, its redistributive effect is modest due to low effective rates (5 to 6% in average with a slight increase throughout the period in two data sources). The latter relates to the dual personal income scheme, the low proportion of taxpayers (see section 3) and the low value of the highest marginal tax rates even for Latin American standards (25% in 2009-2011 and rose to 30% in 2012). For instance, OECD top rates are, in average, 41.5% (Joumard et al., 2013).

Table 8: Tax progressivity and income redistribution indices, 2009-2016

	Year	2009	2010	2011	2012	2013	2014	2015	2016
Tax records	Pre-tax	0.574	0.570	0.565	0.561	0.554	0.552	0.552	0.560
	Post-tax	0.554	0.550	0.543	0.537	0.531	0.529	0.530	0.537
	R-S	0.020	0.021	0.022	0.024	0.023	0.023	0.023	0.023
	Average tax rate	5.0%	5.4%	5.4%	5.6%	5.7%	6.0%	6.0%	6.1%
	Kakwani	0.334	0.331	0.334	0.327	0.328	0.324	0.301	0.293
Harmonized survey	Pre-tax	0.481	0.468	0.452	0.430	0.432	0.429	0.429	0.423
	Post-tax	0.459	0.447	0.432	0.411	0.412	0.409	0.408	0.402
	R-S	0.021	0.020	0.020	0.019	0.020	0.021	0.021	0.021
	Average tax rate	5.1%	4.8%	4.6%	4.6%	5.0%	5.2%	5.3%	5.1%
	Kakwani	0.399	0.406	0.406	0.392	0.39	0.381	0.382	0.304

Note. Own calculations based on tax records (DGI) and household surveys (ECH). First two rows of each panel (tax records and harmonized survey) depict pre and post-tax Gini coefficient. The remaining rows depict standard tax progressivity indices.

As in the case of the Gini and Theil indices, personal income taxation had a constant effect throughout the period, reducing the top 10 and 1% shares in approximately 12-14% and 5-6% (2.5 and 2 percent points respectively), with the subsequent increase at the middle 40% and the bottom 50% (Table 9). At the same time, the post tax participation of the top 0.1% is reduced by 30-45% depending on the year.

To conclude this analysis, we comment on the effective tax rates paid by income source and income centile according to DGI information (Figure 5). As a whole, it can be noticed that total labour earnings depict a progressive scheme, with the minimum taxable income above the median, and respectively reaching 15% at the highest centile and rising to 18% at the top 0.1%. Conversely, capital income rates are steady until percentile 80 and decrease thereafter.

The reasons under this decline refer to the different tax rates within this source depicted in Table A.1: at the top, the relative share of profits increases and this sub-source faces a lower rate than property rents and bank deposits. As a result, tax rates effectively paid by the top 1% are lower, In turn, the same pattern holds for the top fractiles (0.5 and 0.1%). This regressive capital

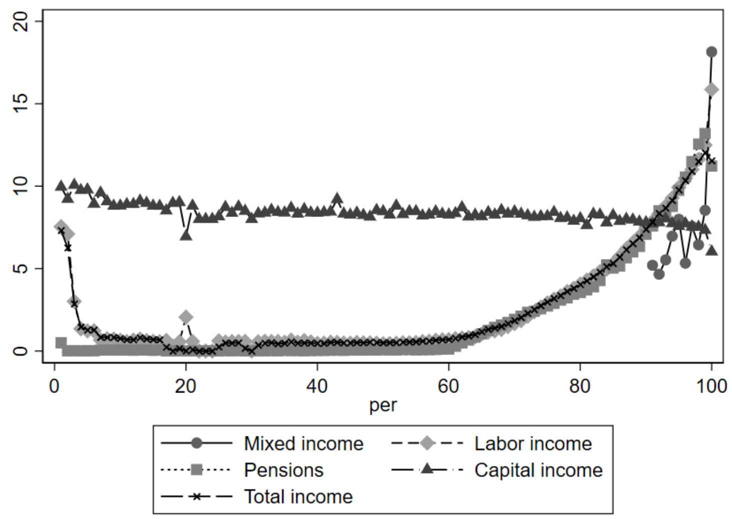
Table 9: Redistributive effect of direct taxation

Inc. Groups	2009	2010	2011	2012	2013	2014	2015	2016
				Post-tax income				
Top 0.1%	3,1	3,7	3,9	3,1	3,8	3,5	3,6	3,5
Top 1%	12,9	13,1	13,3	12,7	12,9	12,8	13,3	14,2
Top 10%	45,1	44,8	44,8	44	43	42,9	43,1	43,9
Middle 40%	44,6	44,7	44,7	45,1	45,7	45,8	45,4	45
Bottom 50%	10,3	10,5	10,5	10,9	11,3	11,3	11,5	11,2
				Change as a % of the pre-tax share				
Top 0.1%	-38%	-27%	-29%	-42%	-32%	-34%	-39%	-45%
Top 1%	-12%	-11%	-12%	-14%	-13%	-12%	-13%	-12%
Top 10%	-5%	-5%	-4%	-5%	-6%	-6%	-6%	-6%
Middle 40%	5%	5%	4%	5%	5%	5%	5%	5%
Bottom 50%	3%	3%	0%	4%	7%	6%	6%	7%

Note. Own elaboration based on tax records (DGI). First panel depicts post-tax income shares. The change in the shares as a result of taxation in terms of the pre-tax income share are presented in the second panel.

income taxation scheme affects total effective rates. Even when they exhibit a progressive pattern for the first 99 percentiles, they fall from 11.5% for the top 1% to 9.5% for the top 0.1%.

Figure 5: Effective tax rates by income source



Note. Own calculations based on tax records (DGI). Effective tax rates for total income and all income sources are depicted.

Although these effective rates are relatively low when compared to OECD countries, they double the estimations for Colombia (Alvaredo and Londoño Velez, 2014). In regard to the potential simulation exercises to inform further tax reforms it is worth pointing out that, consistently with its lower outreach capacity of the higher strata and particularly of capital income, ECH depicts a more progressive pattern at the top fractiles with higher effective rates (12.2% for the top 1% to 13.6% for the top 0.1%) than DGI micro-data.

4.4 Income mobility patterns

The previous subsections presented an overview of the recent evolution of inequality among income earners in Uruguay overlooking individual trajectories. However, it might be argued that if there is enough mobility and income distances are relatively short, individuals might occupy different positions in the income distribution across their lives or within a particular span (Auten et al., 2013; Kopczuk et al., 2010). At the same time, since in previous sections we have shown that the top 1% accrues the same portion of total income that the bottom 50%, persistence in top income positions can be understood as an indicator of the concentration of economic decisions and power. Thus, a complete appraisal of economic well-being disparities requires also examining mobility and its interplay with inequality (Aaberge and Mogstad, 2015; Shorrocks, 1978, 1981).

To address these topics, we exploit the panel structure of DGI micro-data.[25] However, rather than providing a complete picture of intra-generational mobility in a short or medium time-span, our main purposes here are to illustrate the bidirectional links between mobility and inequality, without addressing potential causality issues. We first analyze absolute and positional mobility patterns across the income distribution exploring whether mobility levels varied in the period of larger inequality decline (4.4.1). After that, we explore the extent of persistence in top income positions (4.4.2). Finally, we analyze the distributional effect of income mobility (4.4.3).

4.4.1 Mobility patterns, top income holders and inequality

To analyze mobility patterns, we restricted DGI micro-data to the balanced panel, i.e., those individuals reporting positive incomes in the eight years, leading to exclude 56% of observations.[26] To assess whether mobility patterns relate to the evolution of the income distribution, we split the sample in sub-periods according to the inequality trends identified in previous sections (2009/2013 and 2013/2016).

Annual entry and exit flows at the panel comprise approximately 7% and 5% of individuals respectively (Table A.13). Flows decrease with age and show no particular pattern when disaggregated by gender. As expected, retired individuals exhibits lower entry and exit rates.

[25] Since ECH is a cross-sectional data-set, we restrict our study to the individuals included at DGI micro-data, eliminating the cases we added corresponding to informal workers

[26] Individuals with zero or negative income in at least one period were also excluded. Burdín et al. (2014b) compare the balanced and unbalanced panel for 2009-2012 in terms of individual characteristics and income. As expected, to balance the panel introduces a moderate bias toward older individuals, pensioners and top income earners.

Self-employed workers and capital income earners present larger inflow rates, probably reflecting increasing employment formalization and the expansion of the personal income tax system, respectively.

To assess panel flows patterns regarding individuals' position in the income distribution, we built total pre-tax income vintiles under two variants. The first one was based on the longitudinally-averaged total income in real terms at 2016 prices. Instead, in the second one, we considered individuals' income at the time of entry. In the two cases, entry and exit rates are decreasing in income, particularly until the fourth vintile, where they stabilize (Figure A.2). This result is consistent with the location of the minimum taxable income threshold.

We first estimated average absolute and positional correlations (β coefficients) opened by gender and sub-period under different options, in order to assess the sensitiveness of the coefficients (Tables 10 and A.14). Considering the whole period, the average absolute persistence rate is 0.6, with slight variations by gender (0.62 for women and 0.58 for men). In this case, recalling the results obtained in sub-section 4.4.2, similar mobility opportunities are indicating that women were not able to climb to the higher income strata.

Disaggregations for shorter periods of time yield, as expected, to larger coefficients. In spite of that, a remarkable result is that when comparing sub-periods of similar length, persistence rates are lower during the inequality reduction time-span. Thus, after 2013 estimates yield to extremely high values indicating very low mobility levels. An interesting feature relies in the fact that even when β coefficients are very high and almost converged after redistribution ceased, in the period of inequality reduction the gap among women and men widened in favour of the latter. These results suggest that the gender gap remained steady or even grew throughout the period.

However, ranking based estimations yield approximately 25% higher immobility rates in the 2009-2016 estimations (0.75, 0.76 and 0.74 for the entire population, women and men respectively), suggesting that increased income was not necessarily translated into re-ranking. A second feature of this group of estimations is that, even when the negative association among persistence and inequality reduction still holds, differences across sub-periods were more subtle. At the same time, since coefficients tended to converge, gender distances remained steady or were even reinforced.

The precedent estimations provided a picture for the overall population, without digging into differences by income strata. Transition matrices allow for comparing incomes classes, with the main diagonal providing information on persistence rates, understood as the proportion of individuals remaining in their initial income fractile. Results indicate a remarkable monotonically increasing pattern of persistence at the upper half of the income distribution. Interestingly, approximately 70% of individuals in the 10th decile in 2009 remained in that position seven years later. This value is more than three times higher than the persistence rate exhibited by those individuals in the 5th decile.

Again, there are scarce differences by gender, although, as expected, persistence rates among women are higher in the lower strata and the reverse relation holds above the median (Tables A.16,

Table 10: Intragenerational elasticity. Log of income 2016-2009

	Log of income (final year)					
	2009/2016	2009/2012	2010/2013	2011/2014	2012/2015	2013/2016
Log of income (initial year)	0.603***	0.682***	0.764***	0.764***	0.785***	0.830***
	(0.00113)	(0.00112)	(0.00121)	(0.00139)	(0.00154)	(0.00127)
Observations	1,040,140	1,040,140	1,040,140	1,040,140	1,040,140	1,040,140
R-squared	0.502	0.627	0.696	0.688	0.692	0.674
	Women					
Log of income (initial year)	0.621***	0.710***	0.785***	0.795***	0.808***	0.845***
	(0.00148)	(0.00147)	(0.00150)	(0.00166)	(0.00168)	(0.00145)
Observations	542,810	550,263	545,563	545,656	543,403	541,025
R-squared	0.528	0.655	0.723	0.724	0.724	0.707
	Men					
Log of income (initial year)	0.581***	0.648***	0.732***	0.719***	0.750***	0.835***
	(0.00173)	(0.00172)	(0.00200)	(0.00233)	(0.00277)	(0.00187)
Observations	495,587	489,181	482,111	483,585	479,467	477,069
R-squared	0.461	0.567	0.652	0.632	0.639	0.640

Note. Own calculations based on tax records (DGI). Coefficients of log of income of end year against log of income for base year (with sex, age groups and a dummy for capital income receivers as covariates). In each column, a different set of base/end year is presented. The first panel refers to the whole population, the second restricts the sample to women and the last, to men.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

A.17 A.18 and A.19). Differences by sub-period also reinforce the regression analysis results, with higher mobility, particularly at the top decile and vintile in the period of inequality fall versus the subsequent years (persistence rates at the top decile were 75.2% and 79.7% and rose to 87.4% and 90.7% at the top ventile).

Considering their different incidence across the income distribution, we analyzed the extent of income mobility for different income sources[27], reporting summary mobility indicators from deciles transition matrices (Table A.15). Persistence levels are heterogeneous across income sources and capital income can be singled out as the most mobile income source. Labour earnings appear to occupy an intermediate position in terms of mobility.

Figure 6 plots persistence rates by income source computed as the fraction of individuals remaining either in the same or an adjacent position in the income distribution. Persistence rates increase monotonically from the 10th vintile onward. While labour income mimics the pattern of total income, capital income exhibits a more irregular pattern, since this source becomes noticeable at the top of the distribution. Persistence rises rapidly in top sectors, surpassing labour income at the top 5%.

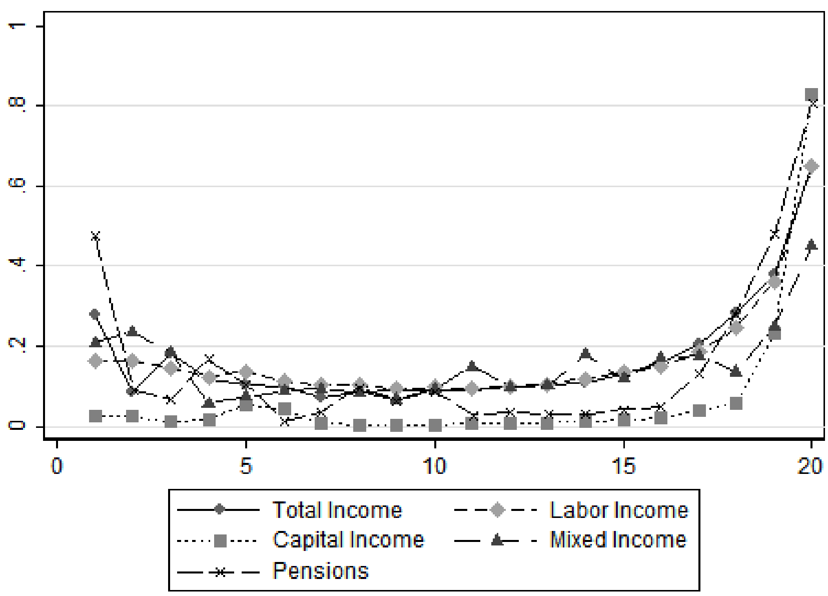
[27]We define individuals earning a given income source as those for whom that source surpasses 50% of their total income.

Table 11: Transition matrix, 2009-2016

	2016											
2009	Decil 1	Decil 2	Decil 3	Decil 4	Decil 5	Decil 6	Decil 7	Decil 8	Decil 9	Decil 10	Top 5	Top 1
Decil 1	32.9%	24.9%	11.1%	9.5%	8.7%	6.8%	4.9%	3.5%	2.4%	1.2%	1.0%	1.0%
Decil 2	36.9%	35.7%	8.7%	6.6%	4.8%	3.6%	2.4%	1.7%	1.1%	0.6%	0.4%	0.5%
Decil 3	7.9%	24.0%	26.6%	9.7%	6.7%	5.0%	3.6%	2.6%	1.7%	0.8%	0.7%	0.9%
Decil 4	6.9%	5.9%	33.6%	23.0%	12.7%	7.9%	5.3%	3.7%	2.3%	1.1%	0.9%	1.1%
Decil 5	5.2%	4.4%	6.9%	31.6%	20.7%	12.7%	8.2%	5.6%	3.5%	1.5%	1.2%	1.4%
Decil 6	3.5%	2.7%	5.9%	7.4%	28.7%	21.7%	13.6%	9.3%	5.4%	2.1%	1.6%	1.8%
Decil 7	2.5%	1.1%	4.1%	5.8%	7.5%	26.8%	25.5%	14.9%	9.1%	3.0%	2.0%	2.1%
Decil 8	1.8%	0.6%	1.8%	4.0%	5.8%	7.8%	24.1%	30.6%	17.9%	5.6%	3.3%	2.8%
Decil 9	1.3%	0.4%	0.9%	1.6%	3.4%	6.0%	8.6%	20.8%	40.6%	16.5%	8.1%	4.9%
Decil 10	1.1%	0.3%	0.6%	0.7%	1.0%	1.8%	3.7%	7.3%	16.1%	67.6%	80.7%	83.7%
Top 5	0.5%	0.1%	0.3%	0.3%	0.4%	0.5%	0.9%	2.6%	3.7%	40.7%	64.9%	77.9%
Top 1	0.1%	0.0%	0.1%	0.1%	0.1%	0.1%	0.2%	0.3%	0.4%	8.6%	15.7%	52.2%

Note. Own calculations based on tax records (DGI). In each cell, the percentage of individuals that were located in a given income group in 2009 (rows) and were part of an income group in 2016 (columns) is depicted. Income groups for both years are the ten deciles of total income, top 5% and top 1%.

Figure 6: Persistence rates 2009-2016



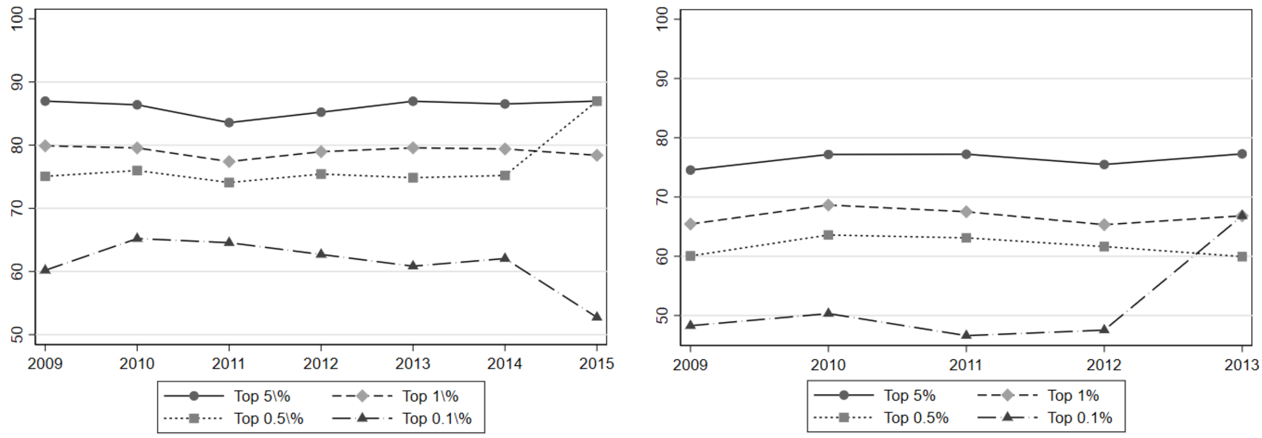
Note. On calculations based on tax records (DGI). Vintiles correspond to 2009 income.

4.4.2 Income mobility at the top

In this section, we scrutinize movements in and out top income groups. Fractile transition matrices indicate that approximately 70% of individuals located in the bottom half of the total income initial distribution remained in the same position in 2016. Barely only 1% of these individuals were able to enter into the top 10%. Similarly, among those in the top 1% in 2009, only 8% moved to the bottom 90% in 2016. Thus, positional changes mainly occurred within the top 10%.

Figure 7 plots the probability of remaining in a certain top income fractile (top 5%, 1%, 0.5% and 0.1%) after one (panel a) and three years (panel b). Annual persistence rates appear to be very stable above 50% in all cases and first three groups surpass 70%. The probability of remaining at the top 5% after 1 year is around 90% and falls to 80% for the top 1%. Persistence rates after 3 years are lower but remain high and stable, except for the top 0.1% that rises at the end of the time span considered. Even when women are underrepresented in these strata, no remarkable differences by gender are found (Table A.4).

Figure 7: Persistence rates in top income fractiles



(a) Persistence after 1 year

(b) Persistence after 3 years

Note. Own calculations based on tax records (DGI). Persistence rates by income fractile after one and three years depicted in panels (a) and (b) respectively. Persistence rates after three years is unconditional on the position held after one and two years. By construction, the larger the group the more likely is that individuals stay in the same group.

The resulting persistence rates for top income groups are in line with previous estimates for developed countries. For instance, the probability of remaining at the top 1% after one year is 78% for Germany (Jenderny, 2016). Moreover, persistence rates at the top 0.1% are around 70%, 60%, and 67% in Germany (2001-2006), Canada (1988-2000) and France (1998-2003) respectively (Jenderny, 2016; Saez and Veall, 2005; Landais, 2008). In the case of Ecuador, Cano (2015) reports average persistence rates of 70% and 60% for the top 1% and top 0.1% respectively.

It is noteworthy that decreasing rates for tinier top fractiles may not necessarily indicate lower persistence in income positions at the very top (Jenderny (2016)). Furthermore, they may also be resulting from a mechanic effect related to different group size. To account for this problem and compare equal-size groups, we computed 2009 total income deciles restricted for the top 1%, 0.5% and 0.1%, respectively. Figure A.5 plots the fraction of individuals who do not move downward between 2009 and 2016. Similarly to Jenderny (2016), the fraction appears to be increasing with the position in the initial distribution within each fractile: individuals belonging to the richest deciles are less likely to move downwards than the remaining fractile members.

4.4.3 Distributive effects of income mobility

Finally, we analyze whether income mobility contributes to reduce long-term income concentration. If annual income partly reflects transitory shocks and relative positions are held by different individuals, we would expect to observe lower income inequality when income is measured over a longer period. Hence, we compare top income shares and inequality indices (Gini y Theil) for each individuals annual and longitudinally-averaged income (Table 12).

The extent of top income mobility appears to be quite modest: a reduction of 0.3 and 0.6 percentage points in the top 1% and top 0.1% income shares respectively. Overall, the equalizing effect of income mobility is limited, indicating a reduction of 2.3 p.p. in the Gini coefficient and 6 p.p. in the Theil index. In this case, there are not substantial differences by sub-period.

Table 12: Annual and average income inequality comparison

	2009-2016			2009-2013			2013-2016		
	Annual	Permanent	Dif (%)	Annual	Permanent	Dif (%)	Annual	Permanent	Dif (%)
Bot.50%	0.159	0.172	-7.6%	0.155	0.161	-3.7%	0.165	0.170	-2.9%
50%-90%	0.445	0.445	-0.2%	0.445	0.444	0.2%	0.445	0.444	0.2%
Top 10%	0.120	0.118	1.4%	0.121	0.121	0.1%	0.117	0.117	0.6%
Top 5%	0.155	0.152	1.8%	0.157	0.157	0.2%	0.151	0.151	0.3%
Top 1%	0.079	0.076	4.5%	0.079	0.078	1.9%	0.079	0.078	0.5%
Top 0.1%	0.043	0.037	16.2%	0.043	0.040	7.7%	0.043	0.040	6.4%
Gini	0.523	0.502	4.2%	0.529	0.519	1.8%	0.514	0.506	1.5%
Theil	0.600	0.539	11.2%	0.612	0.584	4.8%	0.576	0.552	4.3%

Note. Own calculations based on tax records (DGI). In each block, a different set of base/end years. Within each block, income shares (first panel) and inequality indices (second panel) are depicted in two ways: the average index of the period (annual, first column), and the index of the average income of the period (permanent, second column). The third column of each block depicts the difference between the two, as a percentage of the annual estimate.

These results are not surprising considering the high ranking correlations and persistence rates presented in the previous sub-sections. The slight decrease in rank correlations that accompanied the inequality reduction period was not enough to affect long run redistribution. Thus, in the Uruguayan case, relative distances among individuals were shortened but income increases were not enough to carry out a substantial change in positions held at the beginning of the period.

5 Final remarks

As in most Latin American countries, previous studies based on ECH micro-data have shown that Uruguay underwent a substantial inequality fall in recent years, coupled with outstanding economic growth rates. However, analyses for Argentina, Brazil, Colombia and Ecuador assessing top income shares in tax records versus household surveys information present a conflicting picture and cast doubts on the depth and breadth of the inequality fall. The discussion on the "actual" inequality trends is relevant in terms of appraising the relation among economic growth and redistribution as well as the extent of the equalizing effect of redistributive policies such as income taxation, changes in wage-setting institutions and non contributory cash transfer schemes.

To address this issue, we estimate primary income inequality and mobility patterns among the adult population aged 20 and more, based on personal income tax records (DGI) and comparable survey micro-data (ECH). Differently to previous studies for other Latin American countries, we had access to tax-records micro-data for a substantial fraction of the adult population, that allowed to compare both synthetic indices and top income shares. Although levels are substantially higher at DGI micro-data, we found that synthetic indices calculated on the two databases experienced a statistically significant reduction (although milder in DGI tax-records) in 2009-2013 and remained stable after that. At the same time, the income share accrued by the top 1% remained stable or point estimates even grew in tax micro-data whereas it fell according to ECH based calculations.

A closer look at the percentile thresholds in the two databases shows that until the top 10%, ECH captures primary income correctly with a 90% ECH to DGI ratio. However, the lower limit and average income of the upper 1% ECH/DGI ratios have been falling throughout the whole period, which might be consistent with increasing underreporting and refusal rates in ECH resulting from the rapid income increase. Additionally, the income source composition of the top strata at DGI exhibits a growing share of capital income, consistent with the worsening of ECH outreach at the top. Furthermore, between group inequality decompositions singling out the bottom 99% (as a whole or by sub-groups) from the top 1%, suggest that the findings reported in the previous paragraphs are consistent with the patterns of inequality decrease in each data-source.

In fact, whereas in ECH higher income strata experienced higher equalisation levels and led the downwards trend observed in 2009-2013, inequality reduction at DGI was originated in low and middle strata (notably the 50-90%) overcompensating a trend towards increased inequality throughout the whole period at the top. In the last years, inequality reduction at the bottom 99% could not offset the increase at the top. Unlike in DGI data, at ECH inequality reduction was higher at the top than at the bottom 99%. The substantial inequality reduction observed at the top (33% across the whole period) is consistent with its impoverished capacity to reach the more well-off households.

The longitudinal nature of DGI data also allowed to provide a broader assessment of economic disparities by analyzing absolute and relative income mobility. Our findings indicate high persistence rates in positions along the full distribution and, particularly among top income holders. For example, in line with Jenderny (2016) findings for Germany, the average probability of staying at the top 1% in the next year is around 80%. Results show that periods with slightly lowered persistence rates coincide with decreasing inequality trends. However, our results also suggest that over the eight years considered, income mobility has very meagre equalizing effects. Thus, annual cross-sectional inequality measures are a good approximation to long run inequality.

The apparent contradiction between the stability of top income shares and the evolution of Gini and Theil indices calls into discussion several issues related to what kind of inequality is sought to reduce, and broader topics such as the relevance of analysing socio-economic stratification on the basis of a wider scope of variables. It also puts forward the relevance of monitoring and renewing the ways in which household surveys gather information and the need to articulate this information with other valuable data-sources such as tax data.

The interplay between inequality and mobility needs to be further explored in future research. On the one hand, our results might be reflecting that the equalization process shortened relative distances along individuals but it lacked of the necessary strength to promote a substantial re-ranking. On the other, if the departing point was one of high inequality, it is unlikely that increased absolute mobility (as reflected in absolute rankings) can result in substantial re-ranking. Overall, the high persistence of top income positions documented in this study casts doubts on the idea that cross-sectional income concentration at the top reflects a transitory phenomenon.

References

Aaberge, R., Atkinson, A. B., and Modalsli, J. (2013). The ins and outs of top income mobility. *IZA Discussion Paper 7729*.

Aaberge, R. and Mogstad, M. (2015). Inequality in current and lifetime income. *Social Choice and Welfare*, 44(2):217–230.

Altimir, O. (1987). Income distribution statistics in latin america and their reliability. *Review of income and wealth*, 33(2):111–155.

Alvaredo, F. (2010). The rich in Argentina over the twentieth century, 1932-2004. *Atkinson A., Piketty T. and Saez E.(eds.)Top incomes: A Global Perspective. Oxford, Oxford University Press*, 2.

Alvaredo, F. (2011). A note on the relationship between top income shares and the gini coefficient. *Economics Letters*, 110(3):274–277.

Alvaredo, F., Atkinson, A., Chancel, L., Piketty, T., Saez, E., Zucman, G., et al. (2016). Distributional National Accounts (DINA) guidelines: Concepts and methods used in wid. world. *WID. world Working Paper*, 2.

Alvaredo, F., Atkinson, A. B., Piketty, T., and Saez, E. (2013). The top 1 percent in international and historical perspective. *Journal of Economic Perspectives*, 27(3):3–20.

Alvaredo, F. and Gasparini, L. (2015). Recent trends in inequality and poverty in developing countries. In *Atkinson A. and Bourguignon F. (eds.)Handbook of income distribution*, volume 2, pages 697–805. Elsevier.

Alvaredo, F. and Londoño Velez, J. (2014). High income and income tax in Colombia, 1993-2010. *Revista de Economía Institucional*, 16(31):157–194.

Amarante, V., Arim, R., and Salas, G. (2007). Impacto distributivo de la reforma impositiva. background paper for poverty and social impact analysis (psia) of Uruguay.

Amarante, V. and Carella, A. (1997). La captación del ingreso en las encuestas de hogares. *Informe proyecto CSIC de iniciación a la investigación.*

Amarante, V., Colafranceschi, M., and Vigorito, A. (2014). *Uruguay's Income Inequality and Political Regimes over the Period 1981–2010.* Cornia A. (ed.) Falling Inequality in Latin America. Policy Changes and Lessons, WIDER Studies in Development Economics. Oxford University Press.

Anand, S. and Segal, P. (2017). Who are the global top 1%? *World Development*, 95:111–126.

Atkinson, A. B. (2007). Measuring top incomes: methodological issues. *Top incomes over the twentieth century: A contrast between continental European and English-speaking countries*, 1:18–42.

Atkinson, A. B., Casarico, A., and Voitchovsky, S. (2018). Top incomes and the gender divide. *The Journal of Economic Inequality*, 16(2):225–256.

Atkinson, A. B., Piketty, T., and Saez, E. (2011). Top incomes in the long run of history. *Journal of economic literature*, 49(1):3–71.

Auten, G., Gee, G., and Turner, N. (2013). Income inequality, mobility, and turnover at the top in the us, 1987-2010. *American Economic Review*, 103(3):168–72.

Barros, R. P. d. O., Foguel, M. N. O., and Ulyssea, G. O. (2006). Desigualdade de renda no brasil: uma análise da queda recente.

Bergolo, M., Burdin, G., De Rosa, M., Giaccobasso, M., Leites, M., and Rueda, H. (2019). Earnings responses of top labor incomes to tax changes: Evidence from a tax reform in uruguay.

Blanchet, T., Flores, I., and Morgan, M. (2018). The weight of the rich: Improving surveys using tax data. *WID. world Working Paper*, 12.

Bourguignon, F. (2015). Appraising income inequality databases in latin america. *The Journal of Economic Inequality*, 13(4):557–578.

Bucheli, M., Lustig, N., Rossi, M., and Amábile, F. (2013). *Social spending, taxes and income redistribution in Uruguay*. The World Bank.

Burdín, G., De Rosa, M., and Vigorito, A. (2015). Sectores de altos ingresos en Uruguay: participación relativa y patrones de movilidad en el período 2009-2012. *Serie Documentos de Trabajo; 03/15*.

Burdín, G., Esponda, F., and Vigorito, A. (2014a). Desigualdad y altas rentas en el Uruguay: un análisis basado en los registros tributarios y las encuestas de hogares del período 2009-2011. *Jiménez J.P. (ed.) Desigualdad, concentración del ingreso y tributación sobre las altas rentas en América Latina, CEPAL. Santiago de Chile.*, 1.

Burdín, G., Esponda, F., and Vigorito, A. (2014b). Inequality and top incomes in Uruguay: a comparison between household surveys and income tax micro-data. *World Top Incomes Database Working Paper*, 1.

Burkhauser, R. V., Feng, S., Jenkins, S. P., and Larrimore, J. (2012). Recent trends in top income shares in the United States: reconciling estimates from march cps and irs tax return data. *Review of Economics and Statistics*, 94(2):371–388.

Cano, L. (2015). Income mobility in Ecuador: New evidence from individual income tax returns. Technical report, WIDER Working Paper.

Cornia, G. A. (2014). *Falling inequality in Latin America: policy changes and lessons*. OUP Oxford.

Cowell, F. A. and Flachaire, E. (2015). Statistical methods for distributional analysis. In *Handbook of income distribution*, volume 2, pages 359–465. Elsevier.

De Rosa, M., Sinisclachi, S., Vilá, J., Vigorito, A., and Willebald, H. (2018). La evolución de las remuneraciones laborales y la distribución del ingreso en Uruguay; futuro en foco. *Cuadernos Sobre Desarrollo Humano: Montevideo, Uruguay*.

De Rosa, M. and Vilá, J. (2017). Distributional National Accounts for Uruguay 2009-2014: Fallin inequality through the lens of DINA.

Fairfield, T. and Jorratt De Luis, M. (2016). Top income shares, business profits, and effective tax rates in contemporary c hile. *Review of Income and Wealth*, 62:S120–S144.

Feenberg, D. R. and Poterba, J. M. (1993). Income inequality and the incomes of very high-income taxpayers: evidence from tax returns. *Tax policy and the economy*, 7:145–177.

Fields, G. S. and Ok, E. A. (1999). The measurement of income mobility: an introduction to the literature. In *Handbook of income inequality measurement*, pages 557–598. Springer.

Flores, I., Sanhueza, C., Atria, J., and Mayer, R. (2019). Top incomes in chile: A historical perspective on income inequality, 1964–2017. *Review of Income and Wealth*.

Gasparini, L., Bracco, J., Galeano, L., and Pistorio, M. (2018). Desigualdad en países en desarrollo: ¿ajustando las expectativas? *Documentos de Trabajo del CEDLAS*.

Groskoff, R. (1992). Análisis y ajuste de los ingresos investigados por las encuestas de hogares. *Documento de Trabajo*.

Higgins, S., Lustig, N., and Vigorito, A. (2018). The rich underreport their income: Assessing bias in inequality estimates and correction methods using linked survey and tax data.

Jenderny, K. (2016). Mobility of top incomes in g ermany. *Review of Income and Wealth*, 62(2):245–265.

Jenkins, S. P. (2015). World income inequality databases: an assessment of wiid and swiid. *The Journal of Economic Inequality*, 13(4):629–671.

Joumard, I., Pisu, M., and Bloch, D. (2013). Tackling income inequality. *OECD Journal: Economic Studies*, 2012(1):37–70.

Kopczuk, W., Saez, E., and Song, J. (2007). Uncovering the american dream: Inequality and mobility in social security earnings data since 1937. Technical report, National Bureau of Economic Research.

Kopczuk, W., Saez, E., and Song, J. (2010). Earnings inequality and mobility in the united states: evidence from social security data since 1937. *The Quarterly Journal of Economics*, 125(1):91–128.

Landais, C. (2008). Top incomes in France: booming inequalities? *Paris School of Economics, Mimeo.*

Leigh, A. (2007). How closely do top income shares track other measures of inequality? *The Economic Journal*, 117(524):F619–F633.

Lerman, R. I. and Yitzhaki, S. (1985). Income inequality effects by income source: A new approach and applications to the united states. *The review of economics and statistics*, pages 151–156.

López, R., Figueroa, E., Gutiérrez, P., et al. (2013). La 'parte del león': Nuevas estimaciones de la participación de los súper ricos en el ingreso de chile. *Serie Documentos de Trabajo*, 379:1–32.

Lustig, N. et al. (2019). The missing rich in household surveys: Causes and correction approaches. Technical report, Tulane University, Department of Economics.

Lustig, N., López-Calva, L. F., and Ortiz-Juarez, E. (2011). The decline in inequality in latin america: How much, since when and why. *Since When and Why (April 24, 2011).*

Mendive, C. and Fuentes, A. (1996). Diferencias en la captación del ingreso por fuente" en ine. *Taller de expertos sobre medición de pobreza.*

Morgan, M. (2017). Extreme and persistent inequality: New evidence for Brazil combining national accounts, surveys and fiscal data, 2001-2015. *World Inequality Database (WID. org) Working Paper Series*, 12:1–50.

Piketty, T. (2003). Income inequality in France, 1901–1998. *Journal of political economy*, 111(5):1004–1042.

Piketty, T., Yang, L., and Zucman, G. (2017). Capital accumulation, private property and rising inequality in china, 1978-2015. *National Bureau of Economic Research.*

Rodríguez Vivas, M. (2019). Segregación residencial en montevideo: su evolución por variables estructurales para el período 2006-2017. Technical report, Instituto de Economía, Facultad de Ciencias Econ∅micas y Administraci∅n, Universidad de la República, Uruguay.

Saez, E. and Veall, M. R. (2005). The evolution of high incomes in northern america: lessons from canadian evidence. *American Economic Review*, 95(3):831–849.

Shorrocks, A. F. (1978). The measurement of mobility. *Econometrica: Journal of the Econometric Society*, pages 1013–1024.

Shorrocks, A. F. (1981). Income stability in the United States. In *The statics and dynamics of income*. Citeseer.

Shorrocks, A. F. (1999). Decomposition procedures for distributional analysis: a unified framework based on the shapley value. Technical report, mimeo, University of Essex.

Souza, P. H. and Medeiros, M. (2015). Top income shares and inequality in brazil, 1928-2012. *Sociologies in Dialogue*, 1(1).

Székely, M. and Hilgert, M. (1999). What's behind the inequality we measure? an investigation using latin american data. *An Investigation Using Latin American Data (December 1999). IDB-OCE Working Paper*, (409).

Tornarolli, L., Ciaschi, M., and Galeano, L. (2018). Income distribution in latin america: The evolution in the last 20 years: A global approach. *Documentos de Trabajo del CEDLAS*.

A Appendix

Table A.1: Capital incomes tax rates

Income capital	Tax rate
Interests corresponding to bank deposits in Uruguayan currency more than one year lenght and debt titles interests-3 years or more	3%
Interests corresponding to bank deposits in Uruguayan currency less than one year lenght	5%
Dividends and utilities	7%
Housing and mobiliary capital rents	12%
Others rents (sportpersons royalties, author royalties, everlasting rents)	12%

Note. Own elaboration based on DGI (2019).

Table A.2: Labor income tax rates

Income bracket (BPC)	Tax 2009-2011	Income bracket (BPC)	Tax rate 2012-2016
0-84	0	0-84	0
84-120	10	84-120	10
120-180	15	120-180	15
180-600	20	180-600	20
600-1200	22	600-900	22
>1200	25	900-1380	25
		>1380	30

Note. Own elaboration based on DGI (2019).

Table A.3: Pensions tax rates

Pension income bracket (BPC)	Tax rate
0-96	0
96-180	10
180-600	20
>600	25

Note. Own elaboration based on DGI (2019).

Table A.4: Income threshold by fractile, 2009-2016

	2009	2010	2011	2012	2013	2014	2015	2016
Mean	7,711	9,885	11,727	12,925	14,465	14,519	13,717	14,115
P50	4,173	5,401	6,611	7,296	8,449	8,574	8,166	8,315
P90	16,639	21,137	24,534	27,107	29,845	29,826	27,693	28,229
P99	51,488	64,990	75,889	83,947	90,048	90,614	85,670	89,084
P995	71,273	89,879	104,658	115,418	124,411	127,750	120,874	129,563
P999	152,646	195,161	234,337	249,884	276,572	284,969	279,407	323,495
P9995	214,476	280,035	335,945	352,553	382,714	404,714	407,687	483,031
P9999	509,210	636,527	795,509	888,552	1,014,507	1,080,096	1,144,089	1,427,661
Mean top 0001	1,504,618	2,030,844	2,919,147	2,879,033	3,730,341	3,149,241	3,465,832	3,569,248

Note. Own elaboration based on tax records (DGI).

Table A.5: Number of taxpayers by income source

		2009	2010	2011	2012	2013	2014	2015	2016
Labor income	Total	1,187,913	1,183,629	1,237,034	1,222,505	1,272,881	1,297,408	1,313,961	1,310,285
	Taxpayers	315,300	347,001	395,207	416,318	471,838	510,567	753,705	770,127
Employed	Total	1,127,943	1,111,782	1,161,260	1,143,757	1,190,855	1,216,827	1,253,834	1,237,214
	Taxpayers	276,664	300,461	345,480	363,546	416,530	454,957	706,868	715,150
Self employed	Total	51,024	53,489	55,676	54,958	57,956	57,998	40,509	51,705
	Taxpayers	28,760	30,405	31,823	31,684	33,653	34,957	36,533	44,843
Irae	Total	3,504	3,607	3,687	3,899	4,016	4,128	3,970	4,338
	Taxpayers	3,173	3,253	3,348	3,503	3,619	3,676	3,516	3,826
Pensions	Total	639,540	661,366	627,764	684,320	690,830	698,594	709,216	715,801
	Taxpayers	102,136	112,445	111,787	137,988	148,749	158,991	170,184	173,867
Capital	Total	261,765	298,431	323,035	390,660	445,263	385,352	586,851	656,789
	Taxpayers	255,697	293,041	318,012	386,745	441,457	380,569	582,905	652,258
Dividends	Total	3,134	3,437	4,539	5,297	5,933	6,752	8,473	9,339
	Taxpayers	3,134	3,437	4,539	5,297	5,933	6,752	8,473	9,339
Real state rents	Total	55,205	55,089	57,759	58,600	61,102	66,076	70,032	73,771
	Taxpayers	50,829	50,711	54,800	57,212	59,969	65,028	69,196	72,905

Note. Own elaboration based on tax records (DGI).

Table A.6: Non nominative capital incomes as a share of total capital incomes

	Total							
	2009	2010	2011	2012	2013	2014	2015	2016
Interests corresponding to bank deposits in Uruguayan currency or UI, more than one year lengh in local financial institutions	99,8%	100,0%	97,5%	100,0%	100,0%	100,0%	100,0%	100,0%
Interests for bank deposits to one year or more, in Uruguayan currency with no indexation clause	99,9%	100,0%	98,3%	100,0%	100,0%	100,0%	100,0%	100,0%
Obligations and other debt titles interests-3 years or more	41,2%	34,2%	48,1%	96,2%	74,6%	97,6%	91,1%	79,6%
Remaining financial and mobiliary capital rents	62,9%	52,2%	47,4%	59,2%	54,4%	44,3%	49,1%	48,1%
Dividends and utilities	31,3%	39,3%	42,7%	47,2%	38,7%	39,3%	36,9%	34,6%
Sportpersons royalties	10,4%	2,5%	54,0%	8,8%	13,4%	-11,8%	0,9%	-4,4%
Author royalties	-73,0%	-73,7%	-51,8%	-70,0%	-63,0%	-62,4%	-64,3%	-64,3%

Note. Own elaboration based on tax records (DGI).

Table A.7: Owners' withdrawals - added individuals, 2009-2016

Year	Withdrawing profits	Top-labour income earners	Additional individuals	Additional individuals (% tax records)	Tax record	Survey population
2009	1070	3284	1552	0.09%	1721207	759168
2010	1611	2747	1034	0.06%	1722902	742245
2011	2150	3015	1350	0.08%	1758779	696426
2012	2280	3291	1390	0.08%	1793012	686455
2013	2975	3470	1435	0.08%	1852341	685052
2014	3430	3800	1611	0.08%	1928833	674913
2015	5107	4183	1865	0.10%	1916230	690735
2016	6448	5002	2202	0.11%	1923850	707894

Note. Own elaboration based on tax records (DGI).

Table A.8: Gini index's confidence intervals, tax recrods and harmonized survey, 2009-2016.

	Gini Index											
	Tax records						Harmonized survey					
	Pre-tax			Post-tax			Pre-tax			Post-tax		
Year	Point est.	Lower	Upper	Point est.	Lower	Upper	Point est.	Lower	Upper	Point est.	Lower	Upper
2009	57,4%	57,1%	57,8%	55,4%	55,1%	55,8%	48,1%	48,0%	48,2%	45,9%	45,9%	46,0%
2010	57,0%	56,6%	57,4%	55,0%	54,6%	55,3%	46,8%	46,7%	46,8%	44,7%	44,7%	44,8%
2011	56,5%	55,9%	57,0%	54,3%	53,7%	54,9%	45,2%	45,1%	45,2%	43,2%	43,2%	43,3%
2012	56,1%	55,6%	56,6%	53,7%	53,3%	54,2%	43,0%	42,9%	43,0%	41,1%	41,0%	41,1%
2013	55,4%	54,8%	56,0%	53,1%	52,5%	53,8%	43,2%	43,1%	43,2%	41,2%	41,1%	41,2%
2014	55,2%	54,9%	55,5%	52,9%	52,6%	53,2%	42,9%	42,9%	43,0%	40,9%	40,8%	40,9%
2015	55,2%	54,8%	55,7%	53,0%	52,5%	53,4%	42,9%	42,8%	43,0%	40,8%	40,7%	40,9%
2016	56,0%	55,6%	56,4%	53,7%	53,3%	54,1%	42,3%	42,2%	42,4%	40,2%	40,2%	40,3%
2009-2016	*			*			*			*		
2009-2013	*			*			*			*		
2013-2016	n.d			n.d			*			*		

Note. Own elaboration based on tax records (DGI) and household survey (INE). (*) refers to statistically significant variations in the period.

Table A.9: Inequality indices, pre and post-tax, by source, 2009-2016

	Gini Index				Theil Index			
	Tax records		Harmonized survey		Tax records		Harmonized survey	
Year	Pre-tax	Post-tax	Pre-tax	Post-tax	Pre-tax	Post-tax	Pre-tax	Post-tax
2009	0.574	0.554	0.481	0.459	0.712	0.638	0.451	0.401
2010	0.570	0.550	0.468	0.447	0.710	0.635	0.409	0.366
2011	0.565	0.543	0.452	0.432	0.730	0.658	0.375	0.336
2012	0.561	0.537	0.430	0.411	0.709	0.611	0.319	0.288
2013	0.554	0.531	0.432	0.412	0.711	0.638	0.331	0.296
2014	0.552	0.529	0.429	0.409	0.676	0.606	0.329	0.293
2015	0.552	0.530	0.429	0.408	0.706	0.637	0.338	0.299
2016	0.560	0.537	0.423	0.402	0.734	0.663	0.320	0.284

Note. Own calculations based on household survey (INE) and tax records (DGI).

Table A.10: Inequality decomposition among income groups, 2009-2016.

	2009	2010	2011	2012	2013	2014	2015	2016
				Tax records (DGI)				
Gini index	0,574	0,570	0,565	0,561	0,554	0,552	0,552	0,560
Between	0,510	0,506	0,502	0,498	0,492	0,490	0,491	0,499
Within	0,065	0,064	0,063	0,063	0,062	0,062	0,061	0,061
Overlap	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Between (%)	88,8	88,8	88,9	88,9	88,8	88,8	88,9	89,1
Within (%)	11,2	11,2	11,1	11,1	11,2	11,2	11,1	10,9
Overlap (%)	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Bottom 50	0,328	0,323	0,321	0,312	0,314	0,316	0,317	0,322
50 - 90	0,219	0,215	0,208	0,207	0,198	0,196	0,193	0,193
90 - 99	0,173	0,172	0,172	0,170	0,168	0,169	0,172	0,173
Top 1%	0,355	0,364	0,390	0,383	0,400	0,385	0,408	0,423
				Harmonized survey (ECH)				
Gini index	0,481	0,468	0,452	0,430	0,431	0,429	0,429	0,423
Between	0,421	0,409	0,393	0,369	0,373	0,371	0,371	0,365
Within	0,059	0,059	0,059	0,060	0,059	0,059	0,058	0,058
Overlap	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Between (%)	87,6	87,4	86,9	86,0	86,4	86,4	86,5	86,3
Within (%)	12,4	12,6	13,1	14,0	13,6	13,6	13,5	13,7
Overlap (%)	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Bottom 50	0,257	0,248	0,249	0,246	0,238	0,241	0,241	0,240
50 - 90	0,175	0,172	0,166	0,163	0,161	0,158	0,156	0,152
90 - 99	0,155	0,154	0,143	0,128	0,134	0,136	0,137	0,137
Top 1%	0,260	0,214	0,199	0,127	0,174	0,177	0,188	0,171

Note. Own calculations based on tax records (DGI) and household surveys (ECH). The table is divided in two panels, depicting tax records and harmonized surveys respectively. By construction, both micro-data bases refer to the same individuals and same incomes (pre-tax and formal total personal incomes). In each panel, Gini index is decomposed in *between* and *within* components, among the groups defined.

Table A.11: Pre-tax distribution by source and fractile, 2009, 2013, 2016.

	Labor income	Pensions	Mixed income	Capital income	Dividends	Rents	Others
				2009			
Bot. 50%	53,6%	45,0%	0,0%	1,3%	0,0%	1,0%	0,2%
Mid. 40%	72,3%	25,4%	0,1%	2,2%	0,0%	1,4%	0,8%
Cent. 90-99	76,1%	18,1%	0,7%	5,1%	0,3%	2,8%	2,0%
Top 1%	59,4%	3,3%	6,5%	30,8%	8,0%	8,2%	14,4%
Top 0,1%	32,3%	0,4%	7,5%	59,8%	17,7%	14,1%	28,1%
Average	69,3%	22,8%	1,1%	6,8%	1,2%	2,7%	2,9%
				2013			
Bot. 50%	50%	46,3%	0,0%	1,8%	0,0%	1,2%	0,6%
Mid. 40%	40%	22,6%	0,1%	2,5%	0,1%	1,3%	1,1%
Cent. 90-99	75,0%	18,6%	0,8%	5,7%	0,9%	2,8%	2,0%
Top 1%	51,3%	3,3%	6,0%	39,4%	17,3%	8,0%	14,2%
Top 0.1%	21,8%	0,5%	5,0%	72,7%	32,3%	12,0%	28,4%
Average	68,4%	22,2%	1,1%	8,3%	2,7%	2,6%	3,0%
				2016			
Bot. 50%	50%	47,6%	0,0%	2,0%	0,1%	1,4%	0,5%
Mid. 40%	40%	22,4%	0,1%	2,3%	0,1%	1,5%	0,6%
Cent. 90-99	74,7%	18,3%	0,6%	6,4%	1,3%	3,3%	1,8%
Top 1%	49,4%	2,3%	5,5%	42,8%	19,9%	7,6%	15,2%
Top 0.1%	26,3%	0,3%	5,1%	68,3%	32,0%	8,5%	27,8%
Average	67,7%	21,8%	1,0%	9,5%	3,4%	2,9%	3,1%

Note. Own elaboration based on tax records (DGI). Income composition by income groups is depicted in three panels, which correspond to the years 2009, 2013 and 2016. For each year, bottom 50%, middle 40%, top 10% (excluding top 1%), top 1% and top 0.1% are depicted. By construction, the first four groups of each panel account for the entire population. Total income is disaggregated in labor income, pensions, mixed income and capital income. The latter is turn disaggregated in dividends, rents and other capital incomes.

Table A.12: Gini index decomposition by income source. Harmonized ECH data.

	Year	2009	2010	2011	2012	2013	2014	2015	2016
Sk	Labor inc.	0.759	0.755	0.757	0.762	0.757	0.757	0.756	0.742
	Pensions	0.209	0.214	0.216	0.214	0.217	0.217	0.219	0.233
	Capital inc.	0.032	0.031	0.028	0.024	0.027	0.027	0.025	0.025
Gk	Labor inc.	0.642	0.633	0.623	0.613	0.607	0.607	0.612	0.614
	Pensions	0.803	0.800	0.794	0.793	0.791	0.791	0.791	0.779
	Capital inc.	0.981	0.980	0.978	0.980	0.978	0.978	0.979	0.977
Rk	Labor inc.	0.867	0.861	0.861	0.860	0.858	0.857	0.854	0.845
	Pensions	0.246	0.238	0.207	0.182	0.186	0.177	0.189	0.189
	Capital inc.	0.668	0.663	0.596	0.586	0.698	0.593	0.597	0.592
Share	Labor inc.	0.872	0.871	0.887	0.900	0.912	0.896	0.894	0.887
	Pensions	0.085	0.086	0.078	0.069	0.076	0.069	0.074	0.079
	Capital inc.	0.043	0.043	0.035	0.031	0.013	0.035	0.032	0.034
Change (%)	Labor inc.	0.113	0.116	0.130	0.138	0.142	0.139	0.137	0.145
	Pensions	-0.124	-0.128	-0.138	-0.145	-0.147	-0.148	-0.145	-0.154
	Capital inc.	0.011	0.012	0.008	0.007	0.005	0.009	0.008	0.008

Note. Own elaboration based harmonized household surveys (ECH). Gini index income source decomposition (Lerman and Yitzhaki (1985)) is depicted. k is income source, S is the income share, G is the within source Gini index, R reports the correlation among each income source and total Gini, *share* represents the contribution of each source to overall inequality and *change* is the marginal effect of a 1% increase.

Table A.13: Entry and exit rates by individuals' characteristics

	Entries							Exits						
	2010	2011	2012	2013	2014	2015	2016	2009	2010	2011	2012	2013	2014	2015
Total	9.9%	8.0%	6.5%	5.7%	4.9%	4.2%	3.8%	2.7%	3.0%	3.4%	3.8%	4.4%	5.8%	8.7%
Men	9.8%	7.9%	6.4%	5.7%	4.9%	4.2%	3.3%	2.7%	3.0%	3.4%	4.0%	4.7%	6.2%	9.5%
Women	10.0%	8.0%	6.6%	5.7%	4.9%	4.1%	3.5%	2.7%	2.9%	3.3%	3.6%	4.1%	5.3%	7.7%
<25	29.7%	27.0%	24.0%	23.1%	21.4%	19.9%	19.0%	2.0%	2.5%	3.4%	4.4%	6.1%	9.8%	16.9%
25-35	10.9%	8.0%	5.8%	4.6%	3.7%	2.6%	1.5%	2.1%	2.4%	3.0%	3.8%	4.9%	7.0%	11.3%
35-45	8.5%	6.5%	5.1%	4.1%	3.1%	2.3%	1.4%	2.0%	2.2%	2.8%	3.4%	4.2%	5.8%	9.3%
45-55	7.0%	5.2%	4.3%	3.5%	2.7%	2.0%	1.5%	1.8%	2.1%	2.5%	3.0%	3.6%	4.8%	7.5%
55-65	7.9%	5.2%	4.0%	3.5%	2.7%	2.3%	1.8%	1.7%	1.8%	2.1%	2.1%	2.6%	3.2%	4.5%
>65	2.9%	2.0%	1.4%	1.4%	1.2%	1.3%	2.3%	5.1%	5.4%	5.1%	5.1%	4.5%	4.6%	5.0%
Labor	12.9%	10.4%	8.7%	7.6%	6.5%	5.5%	4.9%	2.0%	2.4%	3.0%	3.7%	4.7%	6.8%	11.1%
Employed (+ 1)	3.5%	2.6%	1.4%	1.2%	1.2%	3.2%	3.3%	0.6%	0.9%	1.4%	1.0%	1.3%	2.0%	11.3%
Employed	10.8%	8.9%	7.1%	6.0%	5.2%	3.3%	2.8%	1.2%	1.4%	1.9%	2.5%	3.5%	5.8%	9.4%
Self-employed	14.2%	11.5%	9.9%	8.6%	7.3%	6.4%	5.7%	2.3%	2.8%	3.5%	4.3%	5.4%	7.5%	12.1%
Both	9.0%	6.7%	4.9%	4.2%	3.1%	5.8%	9.1%	2.1%	2.4%	2.6%	2.6%	3.4%	4.2%	7.2%
Pensions	5.0%	3.5%	2.6%	2.4%	2.1%	2.0%	1.8%	4.2%	4.3%	4.2%	4.2%	3.9%	4.0%	4.3%
Capital	5.3%	7.0%	4.6%	3.8%	2.8%	3.8%	8.0%	5.8%	1.7%	2.7%	2.9%	3.5%	2.4%	4.4%

Note. Own elaboration based on tax records (DGI).

Table A.14: Intragenerational elasticity. Ranking of income 2016-2009

	Percentile of income (final year)					
	2009/2016	2009/2012	2010/2013	2011/2014	2012/2015	2013/2016
Percentile of income (initial year)	0.747***	0.836***	0.857***	0.861***	0.873***	0.862***
	(0.000699)	(0.000596)	(0.000547)	(0.000550)	(0.000535)	(0.000532)
Observations	1,040,140	1,040,140	1,040,140	1,040,140	1,040,140	1,040,140
R-squared	0.611	0.739	0.773	0.777	0.783	0.769
			Women			
Percentile of income (initial year)	0.763***	0.848***	0.871***	0.880***	0.887***	0.874***
	(0.000925)	(0.000780)	(0.000716)	(0.000708)	(0.000708)	(0.000697)
Observations	542,810	550,263	545,563	545,656	543,403	541,025
R-squared	0.629	0.750	0.787	0.796	0.797	0.788
			Men			
Percentile of income (initial year)	0.737***	0.826***	0.851***	0.849***	0.858***	0.846***
	(0.00105)	(0.000910)	(0.000837)	(0.000854)	(0.000818)	(0.000791)
Observations	495,587	489,181	482,111	483,585	479,467	477,069
R-squared	0.581	0.704	0.743	0.742	0.754	0.746

Note. Own calculations based on tax records (DGI). Coefficients of income rank in end year against income rank base year (with sex, age groups and a dummy for capital income receivers as covariates). In each column, a different set of base/end year is presented. The first panel refers to the whole population, the second restricts the sample to women and the last, to men.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.15: Income mobility indices, 2009-2016

	Total income	Labor income	Mixed income	Capital income	Pensions
			All		
Atkinson mobility ratio	0,35	0,42	0,41	0,63	0,20
Determinant index	0,82	0,89	0,89	0,93	0,54
Shorrocks' MET - Prais	0,75	0,80	0,82	0,98	0,52
Average jump	1,54	1,79	1,71	2,46	0,97
			Men		
Atkinson mobility ratio	0,39	0,45	0,41	0,60	0,23
Determinant index	0,83	0,91	0,89	0,91	0,59
Shorrocks' MET - Prais	0,78	0,81	0,82	0,97	0,54
Average jump	1,72	1,90	1,74	2,34	0,99
			Women		
Atkinson mobility ratio	0,31	0,39	0,37	0,55	0,20
Determinant index	0,81	0,88	0,82	0,95	0,53
Shorrocks' MET - Prais	0,73	0,78	0,81	0,90	0,52
Average jump	1,39	1,65	1,54	2,41	0,97

Note. Own calculations based on tax records (DGI). Standard income (in)mobility indices depicted. First column depicts results for total income, whilst the rest present results for all income sources.

Table A.16: Transition matrix, women: 2009-2016

	2016											
2009	Decil 1	Decil 2	Decil 3	Decil 4	Decil 5	Decil 6	Decil 7	Decil 8	Decil 9	Decil 10	Top 5	Top 1
Decil 1	34.5%	18.5%	10.5%	7.7%	7.6%	6.7%	4.9%	3.3%	2.2%	1.1%	2.9%	6.0%
Decil 2	18.0%	31.7%	23.0%	10.7%	6.3%	5.1%	3.5%	2.4%	1.4%	0.8%	1.9%	3.8%
Decil 3	27.8%	36.1%	16.7%	7.2%	4.8%	3.7%	2.5%	1.7%	1.0%	0.5%	1.4%	2.9%
Decil 4	6.0%	5.6%	34.8%	20.2%	13.8%	7.7%	5.1%	3.7%	1.9%	1.1%	2.5%	4.8%
Decil 5	5.0%	3.8%	5.3%	39.3%	19.5%	11.4%	7.4%	4.4%	2.6%	1.3%	2.6%	5.2%
Decil 6	3.4%	2.5%	4.5%	5.8%	33.9%	23.0%	12.0%	8.1%	4.5%	1.9%	3.6%	6.8%
Decil 7	2.1%	1.0%	3.0%	4.7%	6.1%	29.3%	27.2%	14.2%	9.0%	3.0%	4.0%	6.9%
Decil 8	1.4%	0.4%	1.1%	3.0%	4.9%	6.8%	25.8%	32.0%	18.3%	6.1%	4.9%	6.6%
Decil 9	0.9%	0.2%	0.5%	0.9%	2.5%	5.0%	8.1%	22.3%	40.7%	18.2%	9.8%	8.8%
Decil 10	0.6%	0.1%	0.3%	0.4%	0.6%	1.4%	3.2%	7.7%	18.2%	65.8%	63.8%	42.1%
Top 5	0.7%	0.1%	0.2%	0.3%	0.3%	0.5%	0.9%	2.7%	4.5%	40.3%	52.5%	41.9%
Top 1	0.4%	0.1%	0.1%	0.1%	0.1%	0.2%	0.3%	0.4%	0.6%	8.9%	15.4%	26.9%

Note. Own calculations based on tax records (DGI). In each cell, the percentage of individuals that were located in a given income group in 2009 (rows) and were part of an income group in 2016 (columns) is depicted. Income groups for both years are the ten deciles of total income, top 5% and top 1%.

Table A.17: Transition matrix, men: 2009-2016

	2016											
2009	Decil 1	Decil 2	Decil 3	Decil 4	Decil 5	Decil 6	Decil 7	Decil 8	Decil 9	Decil 10	Top 5	Top 1
Decil 1	26.3%	24.8%	10.5%	9.8%	8.7%	6.5%	4.9%	3.8%	2.4%	1.2%	4.8%	9.7%
Decil 2	43.0%	31.8%	7.2%	5.1%	4.0%	2.9%	2.1%	1.7%	1.0%	0.5%	1.7%	3.3%
Decil 3	9.8%	23.0%	30.6%	12.2%	8.5%	6.2%	4.6%	3.4%	2.2%	1.0%	3.0%	5.9%
Decil 4	7.5%	7.1%	25.7%	23.0%	13.2%	8.8%	6.4%	4.7%	2.7%	1.2%	2.9%	5.5%
Decil 5	4.8%	5.6%	8.9%	26.8%	19.2%	13.0%	9.4%	6.6%	4.2%	1.6%	3.4%	6.3%
Decil 6	3.0%	3.7%	7.5%	8.6%	26.4%	19.8%	14.5%	9.5%	5.3%	1.9%	3.3%	5.5%
Decil 7	2.0%	1.8%	5.1%	6.4%	8.3%	26.2%	23.8%	15.1%	8.8%	2.8%	3.7%	5.8%
Decil 8	1.5%	1.1%	2.5%	5.2%	6.1%	8.3%	23.1%	29.7%	17.3%	5.2%	4.9%	7.2%
Decil 9	1.0%	0.6%	1.2%	2.1%	4.4%	6.5%	8.1%	18.6%	41.2%	15.8%	8.9%	8.9%
Decil 10	0.8%	0.4%	0.6%	0.8%	1.1%	1.7%	3.0%	6.8%	14.6%	68.3%	62.0%	38.9%
Top 5	0.6%	0.3%	0.4%	0.5%	0.5%	0.7%	0.9%	2.6%	3.6%	40.1%	50.0%	35.4%
Top 1	0.3%	0.2%	0.1%	0.2%	0.2%	0.2%	0.3%	0.5%	0.6%	8.3%	12.8%	21.6%

Note. Own calculations based on tax records (DGI). In each cell, the percentage of individuals that were located in a given income group in 2009 (rows) and were part of an income group in 2016 (columns) is depicted. Income groups for both years are the ten deciles of total income, top 5% and top 1%.

Table A.18: Transition matrix, 2009-2013

	2013											
2009	Decil 1	Decil 2	Decil 3	Decil 4	Decil 5	Decil 6	Decil 7	Decil 8	Decil 9	Decil 10	Top 5	Top 1
Decil 1	51.1%	11.8%	10.4%	9.8%	8.0%	5.9%	4.0%	2.6%	1.5%	0.7%	0.5%	0.6%
Decil 2	29.8%	50.9%	7.6%	5.8%	4.2%	2.9%	2.0%	1.2%	0.8%	0.3%	0.2%	0.2%
Decil 3	5.6%	29.0%	28.1%	9.3%	6.1%	4.2%	3.0%	1.9%	1.1%	0.5%	0.3%	0.4%
Decil 4	4.9%	3.2%	39.8%	24.5%	11.3%	6.8%	4.3%	2.8%	1.6%	0.7%	0.5%	0.5%
Decil 5	3.6%	2.3%	5.7%	37.1%	24.6%	11.9%	7.1%	4.3%	2.4%	1.0%	0.7%	1.0%
Decil 6	2.1%	1.5%	4.1%	6.3%	33.4%	26.2%	13.4%	7.8%	3.9%	1.3%	1.0%	1.1%
Decil 7	1.2%	0.6%	2.4%	3.7%	6.2%	31.1%	31.2%	14.5%	7.0%	2.0%	1.3%	1.3%
Decil 8	0.8%	0.4%	1.1%	2.2%	3.7%	6.4%	26.8%	38.1%	16.4%	4.1%	2.2%	1.6%
Decil 9	0.5%	0.2%	0.4%	0.8%	1.8%	3.4%	6.3%	22.3%	49.9%	14.3%	6.0%	3.0%
Decil 10	0.5%	0.2%	0.3%	0.5%	0.6%	1.0%	1.9%	4.4%	15.4%	75.2%	87.4%	90.4%
Top 5	0.3%	0.1%	0.2%	0.2%	0.3%	0.3%	0.5%	1.4%	2.3%	44.4%	73.2%	86.3%
Top 1	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%	0.2%	0.3%	9.0%	17.1%	63.4%

Note. Own calculations based on tax records (DGI). In each cell, the percentage of individuals that were located in a given income group in 2009 (rows) and were part of an income group in 2013 (columns) is depicted. Income groups for both years are the ten deciles of total income, top 5% and top 1%.

Table A.19: Transition matrix: 2013-2016

	2016											
2013	Decil 1	Decil 2	Decil 3	Decil 4	Decil 5	Decil 6	Decil 7	Decil 8	Decil 9	Decil 10	Top 5	Top 1
Decil 1	45.2%	36.4%	6.4%	4.8%	3.5%	2.2%	1.3%	0.7%	0.5%	0.5%	0.5%	0.6%
Decil 2	27.7%	49.4%	7.9%	3.1%	1.9%	1.1%	0.6%	0.3%	0.2%	0.1%	0.1%	0.2%
Decil 3	7.8%	5.3%	66.2%	14.8%	5.5%	2.9%	1.6%	0.8%	0.5%	0.3%	0.4%	0.6%
Decil 4	6.3%	3.6%	7.1%	55.7%	16.1%	5.9%	2.8%	1.5%	0.7%	0.4%	0.4%	0.6%
Decil 5	4.5%	2.3%	4.8%	9.6%	51.1%	16.7%	6.3%	3.0%	1.2%	0.6%	0.6%	0.8%
Decil 6	3.1%	1.3%	3.4%	5.1%	11.2%	49.6%	16.8%	6.5%	2.4%	0.8%	0.7%	1.1%
Decil 7	2.1%	0.8%	2.0%	3.3%	5.2%	12.4%	49.7%	17.9%	5.5%	1.2%	0.9%	1.2%
Decil 8	1.6%	0.5%	1.1%	2.0%	3.2%	5.2%	13.9%	51.6%	18.3%	2.6%	1.4%	1.5%
Decil 9	1.0%	0.3%	0.7%	1.0%	1.7%	3.0%	5.3%	13.9%	59.4%	13.6%	4.2%	2.5%
Decil 10	0.8%	0.2%	0.4%	0.6%	0.6%	1.0%	1.8%	3.7%	11.2%	79.7%	90.7%	90.8%
Top 5	0.4%	0.1%	0.2%	0.2%	0.2%	0.3%	0.6%	1.2%	2.1%	44.6%	77.3%	87.7%
Top 1	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.2%	0.3%	9.1%	17.5%	66.9%

Note. Own calculations based on tax records (DGI). In each cell, the percentage of individuals that were located in a given income group in 2013 (rows) and were part of an income group in 2016 (columns) is depicted. Income groups for both years are the ten deciles of total income, top 5% and top 1%.

Table A.20: Transition matrix within top 10%, 2009-2016

	2016									
2009	91	92	93	94	95	96	97	98	99	100
91	19.3%	16.2%	15.3%	13.3%	10.2%	8.1%	7.3%	4.5%	3.5%	2.4%
92	21.5%	15.3%	13.9%	12.7%	11.1%	8.9%	5.9%	5.1%	3.3%	2.4%
93	13.4%	21.6%	14.1%	13.3%	11.6%	8.9%	7.1%	5.2%	3.1%	1.7%
94	8.7%	12.0%	22.0%	15.0%	12.4%	10.4%	8.8%	5.1%	3.5%	2.1%
95	5.6%	8.2%	10.9%	21.7%	17.9%	12.4%	9.9%	7.0%	4.3%	2.3%
96	3.0%	4.8%	6.6%	9.6%	20.8%	22.0%	13.8%	9.7%	6.3%	3.5%
97	2.5%	2.5%	4.1%	6.7%	9.5%	20.9%	24.7%	15.4%	9.5%	4.2%
98	1.5%	2.2%	2.5%	3.9%	5.2%	9.3%	21.2%	30.1%	17.4%	6.7%
99	1.2%	1.8%	1.9%	2.5%	3.1%	5.0%	8.1%	22.2%	37.6%	16.7%
100	0.8%	1.2%	1.6%	2.5%	2.2%	3.3%	3.5%	5.7%	18.2%	61.0%

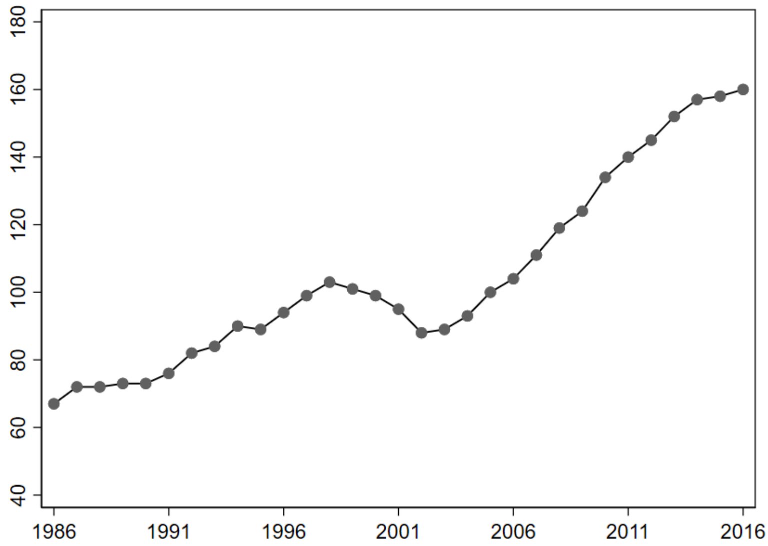
Note. Own calculations based on tax records (DGI). In each cell, the percentage of individuals that were located in a given income group in 2009 (rows) and were part of an income group in 2016 (columns) is depicted. Income groups for both years are the ten centiles of the tenth decile of total income, top 5% and top 1%.

Table A.21: Income Mobility indices (top 10%)

	Total income	Labor income	Employees	Self employed	Capital	Pensions
Atkinson inmobility ratio	0.42	0.45	0.45	0.62	0.61	0.36
Determinant index	0.89	0.96	0.96	0.93	0.97	0.72
Shorrocks' MET - Prais	0.83	0.84	0.84	0.92	0.92	0.81
Average jump	1.76	1.78	1.78	2.63	2.50	1.49
Atkinson inmobility ratio	0.42	0.45	0.43	0.62	0.61	0.36
Determinant index	0.89	0.95	0.94	0.93	0.97	0.71
Shorrocks' MET - Prais	0.82	0.84	0.84	0.92	0.92	0.79
Average jump	1.77	1.81	1.72	2.75	2.55	1.48
Atkinson inmobility ratio	0.42	0.44	0.42	0.62	0.60	0.36
Determinant index	0.88	0.93	0.93	0.86	0.95	0.77
Shorrocks' MET - Prais	0.84	0.85	0.84	0.94	0.92	0.82
Average jump	1.74	1.73	1.62	2.56	2.45	1.50

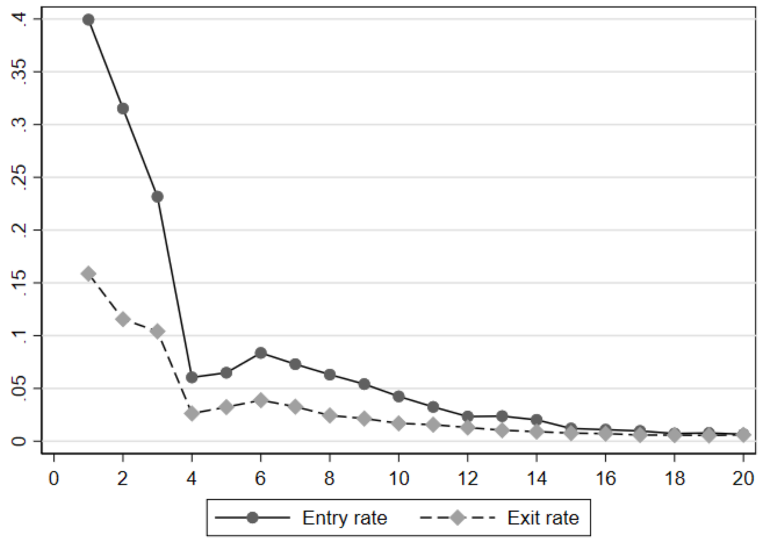
Note. Own elaboration based on tax records (DGI).

Figure A.1: Per capita GDP, 1986-2016 (2005=100)



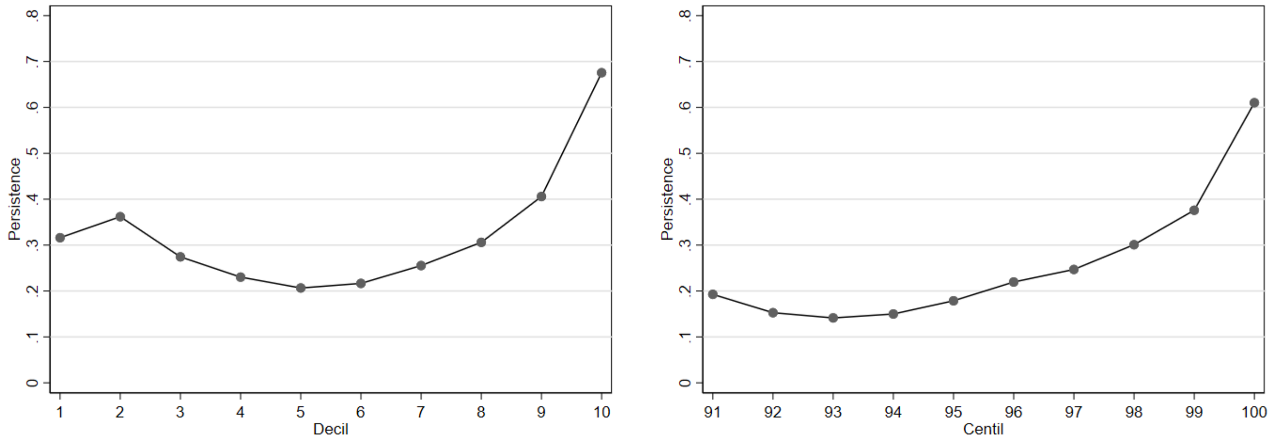
Note. Own calculations based on World Bank data. Base year 2005=100.

Figure A.2: Entry and exit rates by income groups



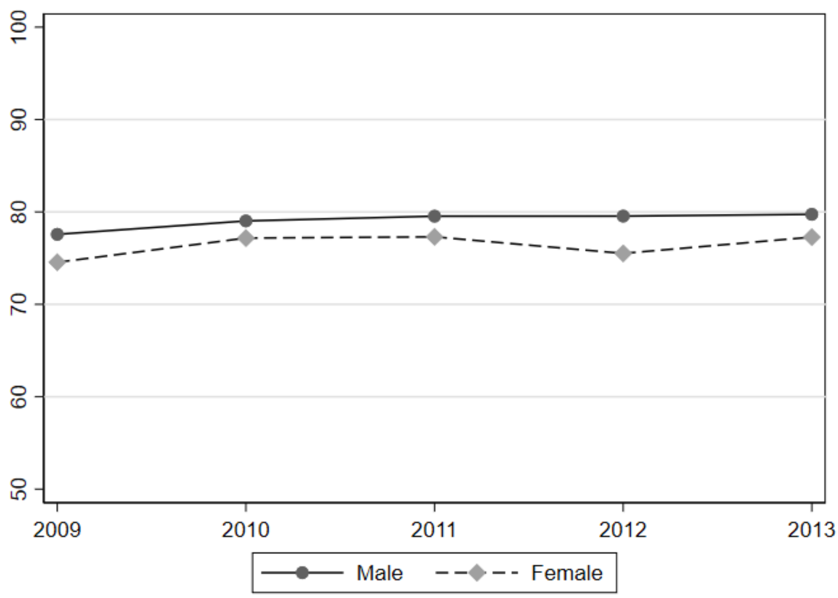
Note. Own calculations based on DGI. Entry and exit rates depicted for 2013; identical results hold for the remaining years.

Figure A.3: Persistence rate by deciles and centiles of the top 10%



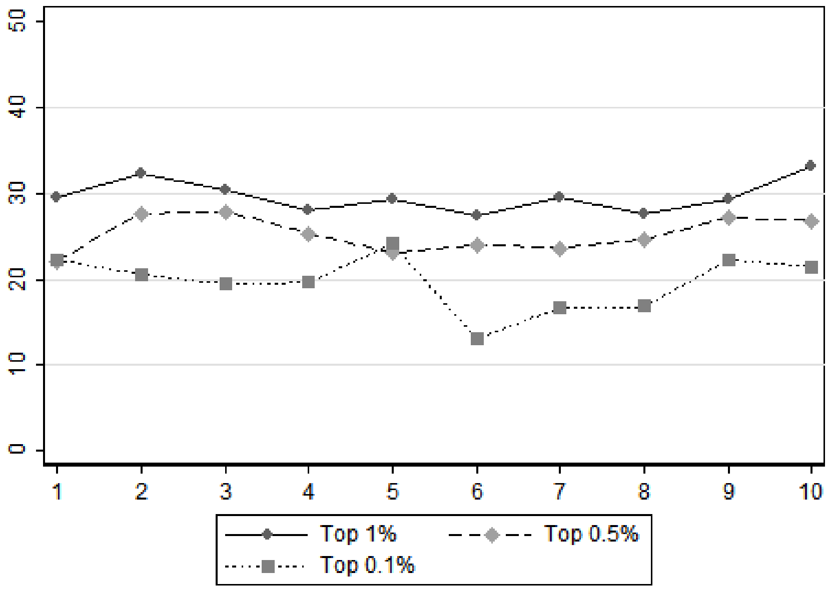
Note. Own elaboration based on tax records (DGI).

Figure A.4: Persistence rates after 1 year by gender (top 1%)



Note. Own calculations based on DGI. Persistence rates after three years is unconditional on fractile membership after one and two years.

Figure A.5: Fraction of individuals who do not move downwards, 2009-2016.



Note. Own calculations based on DGI.Deciles of total income for the Top 1%, 0.5% and 0.1%, computed in 2009 and 2016.