World Development 152 (2022) 105783

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Falling inequality and the growing capital income share: Reconciling divergent trends in survey and tax data

Gabriel Burdín [a], Mauricio De Rosa [b], Andrea Vigorito [c,*], Joan Vilá [c]

[a] University of Leeds, IZA and IECON, FCEA, Universidad de la República, Uruguay
[b] IECON, FCEA, Universidad de la República (Uruguay) and Paris School of Economics
[c] IECON, FCEA, Universidad de la República, Uruguay

ARTICLE INFO

Article history:
Accepted 9 December 2021
Available online 31 December 2021

JEL classification:
D31
H24
O54

Keywords:
Top incomes
Income inequality
Capital income
Tax records
Uruguay

ABSTRACT

In contrast to the remaining regions of the world, the available evidence from household surveys indicates that most Latin American countries experienced substantial reductions in monetary poverty and personal income inequality in the first 15 years of the 21st century. However, it is still unclear whether these trends are robust to the inequality index and database. Based on a unique array of matched social security and personal and firm income tax records, and household survey microdata, we provide detailed evidence on inequality trends for the period of survey-based inequality reduction in Uruguay (2009–2016), focusing on the top income groups and the evolution of the capital income share. We correct administrative data to account for informality and social security/income tax underreporting. Trends are sensitive to the data source and inequality measure. Synthetic indices decreased in both datasets and the top income shares diverged. This results from increasing inequality in the upper tail of administrative data, mainly driven by a growing share of capital income, and particularly dividends. The probability of reaching top income positions is higher for men, liberal professionals, capital income receivers, and occupations associated to medical services. In contrast to evidence for developed countries, the financial and tech sectors are less represented. These findings have strong implications for the design of public policies aimed to reduce persistent inequalities in developing countries.

1. Introduction

In contrast to the remaining regions of the world, the available evidence from household surveys indicates that most Latin American countries experienced substantial reductions in monetary poverty and personal income inequality in the first 15 years of the 21st century (Lustig, López-Calva, & Ortiz-Juarez, 2011; Cornia, 2014; Alvaredo & Gasparini, 2015). While this decline was very fast in 2000–2010, it continued at a milder pace in the subsequent 5 years and, in most cases, ended by 2015 in a context of economic slowdown (ECLAC, 2019; Tornarolli, Ciaschi, & Galeano, 2018).

However, the findings of the top incomes research based on tax returns, both worldwide (Piketty, 2003; Atkinson, Piketty, & Saez, 2011) and in Latin America (Alvaredo & Londoño Velez, 2014; Flores, Sanhueza, Atria, & Mayer, 2019; Morgan, 2017) have reinvigorated the discussion on the validity of household survey data in providing accurate inequality estimates. It is well known that household surveys correctly capture income information of the low and middle strata as well as pension and labour earnings but that they are subject to underreporting and undercoverage at the top end of the distribution and underestimate capital income (Altimir, 1987; Székely & Hilgert, 1999; Cowell & Flachaire, 2015; Bourguignon, 2015; Lustig et al., 2019).

The available literature for developed countries has shown that these draw-backs are particularly important when appraising inequality trends (Piketty, 2003; Atkinson et al., 2011; Jenkins, 2017). Moreover, correctly assessing the evolution of capital income is particularly relevant in a period of rapid economic growth such as the one experienced recently by Latin American countries. If capital income levels or/and shares increased, this phenomenon itself might erode the capacity of household surveys to capture income at the upper tail and could provide a more optimistic view of inequality trends in a region that has been characterized historically by a high concentration of income and wealth

* Corresponding author.
E-mail addresses: gburdin@leeds.ac.uk (G. Burdín), mauricio.derosa@fcea.edu.uy (M. De Rosa), andrea.vigorito@fcea.edu.uy (A. Vigorito), joan.vila@fcea.edu.uy (J. Vilá).

https://doi.org/10.1016/j.worlddev.2021.105783
0305-750X/

(Alvaredo & Gasparini, 2015). Furthermore, the undercoverage of richer strata can lead to wrong evaluations of the redistributive effects of public policies and, in general, of what can successfully reduce inequality. Since persistent inequalities are a major challenge for public policies design, this problem is particularly relevant in the context of developing countries.

Comparisons among household surveys and tax record-based inequality measures are not straightforward due to differences in income definitions and population coverage. Because tax units are individuals in many schemes, top income studies are not able to reconstruct per capita household income, leaving aside homogamy, fertility differentials and other relevant features that affect household conformation and might amplify or mitigate primary income inequality. At the same time, in most cases, administrative data lack information from non-taxable income sources, such as non-contributory cash transfers and other public benefits. Thus, reconciling these two strands of the literature requires access to micro-data from household surveys and tax records to carry out a careful harmonization process (Burkhauser, Feng, Jenkins, & Larrimore, 2012; Burkhauser, Hérault, Jenkins, & Wilkins, 2018).

In this article, we investigate whether the recent inequality fall in Uruguay is robust to the use of different data sets and whether it implies modifications of the shares held by top income groups, and, particularly, capital income receivers. Specifically, we analyse primary income inequality, comparing harmonized household surveys and corrected micro-data from tax records. We provide an in-depth analysis of the main factors underlying the evolution of the income distribution in the two data sets, focusing on the upper tail and the evolution of the different income sources. We delve into the characteristics of the top income earners and the firms that they work for or own, which also allows us to account better for capital income' shares. Uruguay is an interesting case study because we are able to exploit a unique data set of matched social security data and personal and firm income tax records at the individual level that covers the period of significant GDP growth and inequality decrease (2009 to 2016) (Fig. A1).[1]

This research is mainly based on a comprehensive anonymized 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 balance sheets that corresponding firms submitted to the tax authorities (*Dirección General Impositiva, DGI*) in 2009–2016. The latter step is necessary to identify completely the capital incomes and characteristics of employers. Since they include information from social security records, these data cover the universe of formal workers (with earnings below or above the minimum taxable income), capital income earners and pensioners, comprising around 75% of the adult population aged 20 and above. At the same time, we use the micro-data from the official household survey (*Encuestas Continuas de Hogares, ECH*) gathered by the *Instituto Nacional de Estadística (INE)* and a subsample of 2012/2013 ECH-DGI observations linked at the individual level to compute the underreporting rates in the lower tail of administrative data. The broad coverage of our administrative micro-data and the availability of a unique data set of survey-tax data matched at the individual level for a sub-set of households allow us to depart from the tax records and correct the lower half of the income distribution with household survey information, building on the methodology initially proposed by Atkinson (2007). Specifically, we add labour earnings from informal workers and underreported formal income, creating a corrected tax income variable. We also present several robustness checks by correcting harmonized household survey income with tax data (Alvaredo, 2011; Blanchet, Flores, & Morgan, 2018). To identify the main characteristics of top income receivers, we carry out a multivariate analysis exploiting the matched individual-firm databases.

Our findings indicate that the synthetic indexes present declining trends in corrected tax income and harmonized survey income and, in both cases, inequality declined at the bottom 99%. However, the driving forces under the inequality reduction are at odds in the two cases. While the equalization process in the harmonized household survey income was lead by a reduction in the concentration of the top 1%, the opposite applies to corrected tax income, in which the redistribution in the bottom 99% outweighed the increasing inequality at the top. In the latter case, the inverted Pareto coefficient has grown steadily since 2012. As a result, the top income shares exhibit a decline in harmonized household surveys and an increase in corrected personal income tax data.

We also show that the evolution of the top income shares in corrected tax income is closely connected to the increased participation and concentration of capital income in the upper tail of the income distribution. Furthermore, we document that the top income holders are closely connected to the increased share of capital income in the top 1% and 0.5% of the income distribution. Most top income holders are men and capital income receivers. Meanwhile, among the subset of top income earners receiving labour income, the most salient group corresponds to health services.

This study contributes to three main avenues of the existing literature. First, we provide further evidence on the evolution of primary income inequality for a Latin American country. The available top incomes studies for Argentina, Brazil, Chile, Colombia and Uruguay cast doubts on the magnitude of the recent inequality reduction and, in some cases, even on its trend (Alvaredo, 2010; Alvaredo & Londoño Velez, 2014; Flores et al., 2019; Morgan, 2017).[2] Compared with previous studies, we undertake a broader reconciliation exercise. To our knowledge, this is the first study to provide a detailed account of the differences in the evolution of inequality and top incomes in Latin America observed in household surveys and tax records, correcting the lower tail of administrative micro-data to account for underreporting and informal income.

Even though synthetic inequality indices show similar trends in the two data sets, top incomes in the corrected tax income series remained almost steady and slightly grew at the end of the period under analysis. These findings suggest that the Uruguayan redistribution process occurred in the lower and middle strata and coexisted with increasing share and concentration of capital income at the top of the distribution.

Second, we show that household surveys indicate a reduced capacity to reach the top of the distribution, which might be connected to the increasing participation of capital income and the subsequent concentration observed in the upper tail. Although we cannot generalize our results to other Latin American countries, our exercise illustrates the limits of the recent redistributive process and casts doubts on the validity of assessments that rely only on household survey data.

Third, for the first time, we provide evidence of the characteristics of top income earners in a developing country. The scarce representation of women among the top income holders is in line with previous studies on developed countries (Aaberge & Mogstad, 2015; Hansen, Harmenberg, Öberg, & Sievertsen, 2021). However, different from the findings reported by Bertrand and Mullainathan (2001), Bivens and Mishel (2013), Kopczuk and

[1] Household survey information reveals that inequality was constant from 1986 to 1997, started to increase in 1998, peaked with the severe economic crisis in 2002 and remained steady from 2003 to 2008 (Amarante, Colafranceschi, & and Vigorito, 2014).

[2] In the case of Uruguay, previous studies for a shorter time span have also concluded that income inequality estimates based on tax and survey data, although not showing opposing trends, did not fully coincide (Burdín, Esponda, & Vigorito, 2014; Burdín, De Rosa, Vigorito, & and Vilá, 2020). Even though the conclusions are qualitatively similar overall to the ones reached in the present article, the time span was shorter and the data were less comprehensive.

Zwick (2020) and Smith, Yagan, Zidar, and Zwick (2019), top income holders are mainly capital income receivers and the growing share of capital income (and particularly dividends) is the driving force underlying the increase in top income shares. The predominance of capital income in the upper tail of primary income distribution is in line with previous work by Alvaredo, Atkinson, Piketty, and Saez (2013) for Colombia, suggesting that rentiers rather than CEOs hold the top income positions in Latin American countries. Our multivariate analysis shows that the probability of reaching top income positions is higher for men, liberal professionals, capital income receivers, and occupations associated to health activities. In contrast to the findings by Lemieux and Riddell (2015) for Canada, the financial and tech sectors are scarcely represented at the top.

The remainder of this article is organized as follows. Section 2 reviews the 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 presents the main inequality estimates across income definitions and data sources, while Section 5 attempts to reconcile the divergent trends. Section 6 documents the growing share of capital incomes at the top, and presents some distinctive features of the top income groups, and finally Section 7 concludes. Additional information can be found in Appendices.[3]

2. Inequality and top incomes shares in Latin America: recent evidence from survey and tax records data

To overcome the caveats of household surveys' ability to capture top incomes, in the last decades, distributional studies have revivied the tradition of analysing personal income tax records (Feenberg & Poterba, 1993; Piketty, 2003; Atkinson, 2007; Atkinson et al., 2011; Alvaredo et al., 2013). These studies have shown that, even when high income groups by definition represent a very small fraction of the population, not only can the top income share levels and trends be different but also synthetic inequality measures, such as the Gini index, have proved to be sensitive to misreporting and survey undercoverage at the upper tail of the income distribution (Leigh, 2007; Alvaredo, 2011).[4]

However, tax records also present many caveats that have been acknowledged in the related literature. Due to informational constraints, most assessments based on administrative data can only analyse primary income inequality among individuals.[5] At the same time, administrative data are subject to tax evasion and avoidance, as well as behavioural responses to changes in tax rates (Atkinson et al., 2011; Feenberg & Poterba, 1993).[6] The challenges are even larger in developing countries, where informal workers represent a large proportion of the labour force and personal tax systems are not fully developed. Thus, recent studies have moved in two main directions: (i) creating harmonized income variables to carry out accurate comparisons among different data sources to assess inequality trends correctly and (ii) developing methodologies to combine survey and tax data properly.

Regarding (i), Burkhauser et al. (2012) analysed the 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 the administrative data. They found that, once income and tax units are defined consistently across data sources, the differences decrease, even though modifications to the tax system and survey design may explain differential trends in some periods. A limited number of earnings validation studies, relying on survey-tax linked data at the individual level, have identified a mean reversion pattern in reported income, with survey information yielding higher incomes at the bottom of the income distribution and lower values in the upper tail (Abowd & Stinson, 2013; Adriaans, Valet, & Liebig, 2020). This reporting pattern has been associated with cognitive difficulties, social desirability behaviours, off-the-book payments and informality (particularly at the bottom of the distribution).

The recent literature addressing (ii) has been progressing in providing a common ground by developing new methods that combine household survey and tax data to ensure that the upper tail is captured properly (Jenkins, 2015; Alvaredo et al., 2016; Piketty, Yang, & and Zucman, 2017; Anand & Segal, 2017). However, to date, there is no consensus on the "true" distribution, which largely depends on researchers' priors (Abowd & Stinson, 2013), and there is an ongoing discussion on the appropriate correction methods. While some studies have departed from tax data and supplemented them with household survey information, other studies, relying on reweighting and replacing methods, have corrected the upper tail of household survey data with information from tax data and, in some cases, fitted a parametric distribution at the top (see, for instance Jenkins, 2017; Blanchet et al., 2018; Lustig et al, 2019).

In Latin America, the first attempts to correct household survey income underreporting can be traced to Altimir (1987)'s adjustment to national accounts, which was included in the official inequality estimations provided by the Economic Commission for Latin America (ECLAC). However, this methodology has proven to have many caveats (mainly concerning the quality and paucity of national accounts information), and ECLAC discontinued this procedure in 2019.

Despite the longstanding Latin American tradition in distributional studies, research focusing on the top income groups has been less frequent, partly due to scarce data availability and the weaknesses of personal income taxation in the region. To date, there is evidence for Argentina (Alvaredo, 2010), Colombia (Alvaredo & Londoño Velez, 2014), Brazil (Souza & Medeiros, 2015; Morgan, 2017), Chile (López, Figueroa, & Gutiérrez, 2013; Fairfield & Jorratt De Luis, 2016; Flores et al., 2019) and Uruguay (Burdín, Esponda, & Vigorito, 2014; De Rosa & Vilá, 2020). However, most of these studies covered a shorter period than the scholarship on top incomes for developed countries and either relied on tax data tabulations or were based on micro-data that covered taxpayers only or the upper income strata.

In a recent study, De Rosa, Flores, and Morgan (2020) provided inequality estimates for ten Latin American countries by correcting household survey information with tax data (before scaling up to national income components), based on the reweighting methodology developed by Blanchet et al. (2018). They found mixed evidence regarding the recent inequality decline. Specifically, in the cases of Argentina, Colombia, Ecuador and Uruguay, the results are robust to the correction, whereas, in the case of Brazil, the findings are similar those presented by Morgan (2017) (see below).

In-depth studies on specific countries, comparing survey and tax data, have concluded that inequality trends are sensitive to the data source and inequality measure (Table 1). For instance, Alvaredo and Londoño Velez (2014) found that the top income shares in Colombia remained steady (at around 20%) in the period

[3] Appendix 2 is an online supplement that mainly contains additional information on the databases used in this study.

[4] In spite of this, Leigh (2007) argued that the top 1% estimates are a good proxy for Gini index rankings across countries.

[5] Depending on the tax regime and the definition of taxable income, in most cases this information does not allow us to reconstruct households (which might be the relevant unit for many assessments and, particularly, for public policy design) and leaves aside non taxable income sources, such as cash and in-kind transfers.

[6] For instance, Feenberg and Poterba, 1993 assessed the participation of top income groups in the United States based on personal income tax information between 1951 and 1990 and showed that the rise in top income shares was partly driven by a substantial reduction in the top marginal tax rates from 70% to 28% implemented in 1986, which affected the evasion rates at the top.

Table 1
Top income shares and Gini indices in Latin American countries: circa 2000 and 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	26.3/ 27.5%	Morgan (2017)	0.583/ 0.513
	2005/12	22.7/ 26.4%	Souza and Medeiros (2015)	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 the top income share's estimations (primary income) are (Alvaredo & Londoño Velez, 2014; Flores, Sanhueza, Atria, & Mayer, 2019; Souza & Medeiros, 2015; Alvaredo, 2010; Morgan, 2017) . Income shares are calculated according to fiscal income. Gini indices based on household surveys are available from (SEDLAC CEDLAS and The World Bank) and correspond to per capita household income.

in which household survey-based Gini indices fell (2006–2010), even after correcting for underreporting in the upper tail. In turn, Flores et al. (2019) identified opposite trends for Chile, with an increase in tax-based top income shares since 2000 and a decline in household surveys. Souza and Medeiros (2015) analysed the case of Brazil during the period 2006–2012 and concluded that the inequality indices remained steady, with the top income shares representing around 25% of the total income throughout the whole period. However, more striking results came from Morgan (2017), who, using the Blanchet et al. (2018) correction, analysed a longer span and found an increasing trend or, at best, a steady income concentration level in Brazil, contradicting most of the previous research based on household survey data, which unanimously identified a consistent and long period of rapid inequality decline (Lustig et al., 2011; Barros, Foguel, & and Ulyssea, 2006). It is noteworthy that this study also reported 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 on Latin American countries were not able to exploit micro-data for a significant fraction of the population, the corresponding comparisons used the Alvaredo (2011) correction and did not include tax record-based synthetic inequality indices. In sum, the existing evidence on the robustness of the recent decrease in inequality in Latin America is not conclusive.

3. Data and methodology

In this section we first describe the main features of the databases used in this research (3.1) and then present the methods implemented to estimate top incomes shares and the remaining inequality measures (3.2).

3.1. Data

To account for the Uruguayan population aged 20 years and more, we combine personal and firm income tax with household surveys micro-data. Table A.1 summarizes the population coverage and income definition for each data source.

3.1.1. Income tax micro-data

The Uruguayan personal income tax is based on a dual scheme that consists of two separate progressive tax schedules for labour income and pensions (*Impuesto a la Renta de las Personas Físicas (IRPF) cat. II* and *Impuesto de Asistencia a la Seguridad Social*, (IASS)), and a flat tax rate on capital income (IRPF cat. I).[7] There is also a separate corporate income tax scheme that taxes dividends and profits at a 25% flat rate (*Impuesto a la Renta de las Actividades Económicas*, IRAE). The tax schedule remained unchanged throughout the period 2009–2016, except for a relatively small tax increase for the top income brackets in 2012 (the tax rates can be found in Tables A.2.1, A.2.2 and A.2.3).[8]

In most cases, labour taxes are withheld by employers, who transfer the corresponding payments to the Social Security Institute (*Banco de Previsión Social, (BPS)*). Only the self-employed or those workers with more than one occupation (and an annual income above 16,000 USD) have to file a tax return. Self-employed workers contribute for their full (non salaried) labour income and are entitled to deduct up to 30% of their income. Although tax units are individuals, married couples can fill a joint labour income tax return however, in practice, only 1.8% of taxpayers choose this regime.

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 contained detailed information on capital, pension and labour income for each occupation, tax burden and deductions (Table A.2.4); (b) the universe of monthly labour income and pensions payments from social security records (provided to the DGI by the BPS) corresponding to formal workers and pensioners.[9] As the BPS withholds income tax payments for workers and pensioners, DGI information comprises pensioners and the universe of workers contributing to social security, regardless of whether they are net tax-payers. At the same time, each record contains information on sex, age, industry and type of employer (salaried or self-employed). Additionally, DGI provided a supplementary database with information on income and taxes corresponding to the personal services societies that chose to pay corporate income tax (IRAE) instead of IRPF (see the IRAE row in Table A.2.4). This option is available for liberal professionals and, thus, these earnings can be assimilated either to mixed or to income. The resulting micro-data covers 75% of the population aged 20 years and above.[10]

We group capital income into the following categories: profits and dividends, real estate rents, interest from bank deposits and other concepts (sports persons royalties, authors royalties and everlasting rents). Like most top incomes studies, we exclude capital gains from our analysis. Due to the Bank Secrecy Act and to previous regulations that allowed firms to issue bearer shares, we do not have access to micro-data on interests from bank deposits and non-nominative dividends.[11] Table A.2.5 shows that while interest is not a relevant concern, non-nominative dividends account

[7] 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, it was restored in 2006. Although pensions were originally included in IRPF, soon after the reform this component was declared unconstitutional. As a result, a new progressive tax on pensions with similar characteristics was passed in July 2008 (IASS).*

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

[9] The Uruguayan fiscal year corresponds to the calendar year.

[10] The remaining 25% corresponds to informal workers (38.9%), and people who are unemployed (10.9%) or out of the labour force, who are not receiving pensions or capital income (50.2%).

[11] Non nominative dividends are profits distributed by firms of which the owners are anonymous, and, thus, it is not possible to identify the receiver in DGI data-base. The DGI provided the total amount of dividends that fall into this category.

for half of the total dividends.[12] Since we lack information on the characteristics of non-nominative profit receivers, to minimize the potential reranking among capital earners, we distribute the total amount among individuals in the tax record micro-data proportionally to the total capital income held by each individual.[13]

It is worth pointing out that the analysis presented in this article excludes dividends accrued by non residents. From Table A.2.6, it is apparent that, as many firms are owned by international corporations and non-residents, a significant fraction of the profits generated in Uruguay are taxed according to a different scheme, the *Impuesto a la Renta de no Residentes* (IRNR).[14] Notice that throughout the period, assuming an IRNR tax rate of 12%, dividends remitted abroad represented between 1.3 and 4 times those held by residents. Compared with the full amount of capital income, these shares varied between 57% and 80%. These figures suggest that a substantial proportion of the capital income generated in Uruguay does not remain in the country.

Even if tax records are available, identifying capital income correctly can be difficult due to the design of the tax systems and particularly the interplay between firm and personal income taxation.[15] It is noteworthy that in Uruguay, firms were allowed to keep undistributed profits that were not reinvested without any time limit until 2017. Thus, to avoid filing a personal income tax return declaring distributed profits or dividends (taxed at a 7% rate additional to the 25% rate on corporate income), many firm owners took cash advances. As these withdrawals have to be singled out on balance sheets as a separate concept, *advance payments*, we are able to partially reconstruct the actual distribution of capital income had these payments in advance been declared as distributed profits.[16] Unsurprisingly, our estimations convey a low number of profit withdrawals per year (fewer than 10% of the firms distributed benefits). Nevertheless, throughout the whole period, the total amount of profit withdrawals in DGI is considerably higher than the amount that we obtain in ECH. As shown in A.2.8, in 2009 and 2016, individuals receiving in advance payments respectively represented 188% and 146% relative to distributed profits.

As in most tax record based research, in Uruguay tax units are individuals and we cannot reconstruct households. Because they are not included in the taxable income definition, we also do not consider relevant income sources such as the value of owner-occupied housing and private and non-contributory public transfers.[17]

3.1.2. The Uruguayan household surveys

The National Statistical Office (INE) gathers household survey (*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 employment characteristics, socioeconomic variables and personal income by source. The sample design and further methodological details can be found in Instituto Nacional de Estadística (2021).[18]

After-tax labour income is gathered for each household member aged 14 years or above, including cash and in-kind payments for salaried workers, self-employed workers and business owners (separately recording the main occupation and the remaining ones). The survey also collects information on the contributory status of employed workers in each occupation. After tax pensions are collected separately for each individual.

The questionnaire also collects interest, dividends, rents, benefits and the imputed value of owner occupied housing. Except for profit withdrawals reported by self-employed workers 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.

As in other regions, the accuracy of household surveys in capturing incomes has been the subject of a longstanding discussion in Latin America (Altimir, 1987; Székely & Hilgert, 1999). In the same vein, during the 1990s, several studies analysed the accuracy of ECH in capturing household income by source compared with the national accounts and expenditure surveys (Groskoff, 1992; Mendive & Fuentes, 1996; Amarante & Carella, 1997). More recently, Amarante, Arim, and and Salas (2007) found that ECH captures 39.7% and 23% of the total amount of housing rents and interest on bank deposits. Based on an ECH subsample of households with children aged 0 to 3 that gathered ID numbers and was merged with tax records, Higgins, Lustig, and Vigorito (2018) and (Flachaire et al., 2021) harmonized household survey formal income to make it comparable with tax records, and identified the expected misreporting pattern (Abowd & Stinson, 2013): underreporting in DGI income below the median and underreporting in ECH income thereafter. For the top 1%, ECH captures around 56% of DGI income.

Thus, if we only correct DGI income to account for informal income, we are still losing misreported formal income at the bottom of the distribution and we could overestimate inequality. To account for this problem, we also use information from the Nutrition, Child Development, and Health Survey (*Encuesta de Nutrición, Desarrollo Infantil, y Salud*, ENDIS; (Instituto Nacional de Estadística, 2013; Instituto Nacional de Estadística, 2021)). ENDIS follows households with children aged 0 to 3 that were originally included in ECH between February 2012 and August 2013 and gathered information on the unique national identification number (*cedula*) of the respondents, and, in this way, INE and DGI were able to merge all adults from the 2012–13 ECH that were also in ENDIS, to tax records and provided an anonymized data-set for research purposes. 1,471 individuals have positive harmonized formal income in the two datasets and are the ones we use to compute

[12] In recent years, to comply with the international regulations set by the Basel Agreement, Uruguay has restricted the issuance of bearer shares. In spite of this policy change, the share of non-nominative dividends remained steady in the period under analysis. Thus, potential trespassing from non-nominative to nominative profits does not seem to be a relevant concern here.

[13] As shown by De Rosa, Sinisclachi, Vilá, Vigorito, and Willebald (2018), very few firms declare distributed profits. Therefore, imputing non-nominative profits only to nominative profit receivers, is likely to overestimate the concentration of capital income. By distributing it in proportion to the total capital income, the capital income distribution remains unchanged.

[14] In 2008, the annual influx of foreign direct investment was around 5.5% of the GDP (Bittencourt, Carracelas, Doneschi, & and Reig Lorenzi, 2009; Chudnovsky & López, 2007). In the time span covered in this study, at least 13% of the firms were owned by non-residents (Peluffo, 2015).

[15] For instance, in their study on Chile, Fairfield and Jorratt De Luis (2016) and Flores et al. (2019) used information from individuals and firms tax returns and imputed accrued profits and accumulated undistributed profits to taxpayers using ownership shares that were directly estimated from businesses tax-return forms. These studies indicated that although the inequality levels are extremely sensitive to this procedure, trends do not vary.

[16] However, corporate tax declarations and balances are available only for the subset of firms with revenues above US$40.000 per month (around 60% of registered firms).

[17] Many studies indicate that both factors are relevant in Latin America. Besides, the increased coverage of cash transfers contributed to the recent reduction of inequality (Lustig et al., 2011; Cornia, 2014; Alvaredo & 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 personal income tax (Bucheli, Lustig, Rossi, & Amábile, 2013; Amarante et al., 2014).

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

differences in labour earnings from formal occupations (see Flachaire et al., 2021 for details).

To harmonize ECH information with the income tax micro-data, we compute formal and informal labour earnings, pensions and capital income on an individual basis and restrict income sources to the ones captured by DGI micro-data according to the definition of taxable income (see Appendix B for details). Additionally, we use two ancillary tables created using ECH data. The first one is computed on the basis of the ECH-ENDIS linked tax data sub-sample and contains misreporting ratios by tax income percentile and available for 2012/2013 only. The second one identifies the extent of overlapping among formal and informal income in ECH by computing informal/harmonized formal income in ECH ratios using DGI percentile tax thresholds for each year.

3.2. Variables of interest: corrected income and population control

As we are particularly concerned with reconciling inequality trends in household surveys and tax data, and the previous literature has pointed out that the differences rely heavily on undercoverage of the upper tail, we depart from DGI data and supplement it with ECH information to account better for informal income and misreporting in the lower tail. This option is feasible because of the wide population coverage of DGI data. Furthermore, as mentioned in previous sections, evidence from Uruguayan linked data suggests that since underreporting starts in the median of the income distribution, the advantages of departing from the household survey are not clear as we are not attempting to reconstruct households, use ECH covariates or assess the impact of redistributive policies targeting the lower tail of the distribution.

Thus, adapting the methodology to estimate the top income shares based on tax records developed by Atkinson (2007), we depart from tax data and add survey information to create full income distributions that allow us to compute income and population control totals, quantile shares and synthetic inequality measures. We also carry out two robustness checks by correcting survey data with tax information to account for underreporting in the upper tail, implementing the corrections proposed by Alvaredo (2011) and Blanchet et al. (2018).

3.2.1. Population control

Since tax micro-data represent formal workers, capital income earners and pensioners, computing of income shares (and inequality measures in general) requires the definition of a reference population. The standard practice in top incomes research is to consider the population projections of individuals aged 15 to 20 years and above. Since most top income studies on Latin America consider the latter, we follow this practice. Besides, the number of observations in DGI micro-data in the age interval 15–19 is extremely low.

Uruguayan tax records account for around 75% of the population aged 20 and above (Table 2).[19] As we show in detail in Section 3.2.2, we carry out a set of adjustments to account for the total number of income earners and adults in labour force.

3.2.2. Income variables

Atkinson et al., 2011 proposed two main methods to estimate top incomes shares when tax data are available. Departing from the population control, most top income studies used the first variant and estimated the total income held by a certain quantile according to tax records and compared it to National Accounts System (SNA) information on income totals. However, in Uruguay national income estimations by institutional sector were discontinued from 1997 to 2012. In addition, we are able to work with social security records matched with personal income tax records combined with firms micro-data. Thus, our preferred option is the second procedure proposed by Atkinson (2007), that can be used when administrative data have a large coverage of the population control, as in the case of the Netherlands. This method combines tax and survey micro-data (henceforth Method 1). To check the robustness of our results, we also use the limited SNA information for the sub-period 2012–2016 (henceforth Method 2).

Based on corrected DGI micro-data, we computed the pre and post-tax top income shares, the synthetic inequality indices (Gini and Theil) and the corresponding between group and income source decompositions (Shorrocks, 1981; Lerman & Yitzhaki, 1985; Shorrocks, 1999; Boschini, Gunnarsson, & Roine, 2020). We also include confidence intervals, calculated by boostrapping the corresponding inequality measures.

Fig. 1 presents a general overview of the steps that we follow to create the set of corrected income variables and aggregates used in this study. The main purpose of our correction is to adjust the lower tail of the tax records distribution, in order to account for informal and simultaneous formal/informal income. Thus, we depart from the tax records database (Y_{tax}) that includes the universe of individuals receiving formal labor, capital and pension income and add up ECH observations corresponding to purely informal workers and non income receivers with their respective survey weights and expansion factors (Step 1). However, as a proportion of individuals might switch from informal to formal work, the total number of individuals we get is larger than the population control. Hence, to fit the total number of observations to the actual value of the population projections, we perform two alternative adjustments to assess the sensitivity of our results (Step 2). In the first option, we only downsize the number of purely informal individuals that were added from the survey (Y_1), while, in the second alternative, we also adjust each DGI individuals by the number of months of formal labour income received (Y_4). Next, using the misreporting ratios obtained upon the linked data, we inflate DGI earnings to account for formal labour income underreporting in the lower tail of the tax record distribution obtaining Y_2 and Y_5 (Step 3). Up to this point, we included pure informal individuals and corrected formal labour income but we still do not account for individuals that jointly receive formal and informal labour income. Thus, in a final step, based on the proportion of informal to formal labour income reported by ECH respondents, we add a second imputation to the corrected labour earnings vector, creating Y_3 and Y_6 (Step 4). In the remaining of this subsection, we describe each step in detail.

In Step 1, we depart from the tax records' income variable, Y_{tax}, and include ECH observations corresponding to individuals aged 20 or above who have zero harmonized income in ECH (Y_{survey}) - that is, they are not contributing to the social security system (informal labour income) and are not receiving pensions or capital income- with their survey weights. As can be checked in Table 3, the added ECH informal income represents around 6% to 9% of DGI income and, as expected, it is heavily concentrated in the lower tail of the income distribution (Fig. A2.2 panel (a)).

However, as pointed out before this procedure yields a number of observations that exceeds the population total by approximately 10% (Table 2). Thus, in a first variant we compress the survey weights to achieve consistency with the population projections (Step 2). This excess number of observations arises from the fact that this correction implicitly assumes that workers are either formal or informal and do not switch from inactivity or informality to

[19] 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. 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.

Table 2
Population control.

		2009	2010	2011	2012	2013	2014	2015	2016
1	Total population (> 20)	2,348,300	2,370,788	2,390,888	2,410,258	2,430,379	2,451,739	2,474,284	2,497,361
2	Tax unadjusted	1,840,111	1,842,057	1,917,702	1,914,829	1,973,759	2,003,804	2,017,146	2,019,465
3	Survey unadjusted	760,713	743,279	697,776	687,517	686,487	676,524	692,600	710,096
4	Informal	369,224	368,758	338,103	323,440	317,494	313,705	314,273	327,252
5	Inactive	391,489	374,521	359,673	364,077	368,993	362,819	378,327	382,844
6	Total unadjusted (tax + survey)	2,600,824	2,585,336	2,615,478	2,602,346	2,660,246	2,680,328	2,709,746	2,729,561
7	Excess of population (%)	10.8%	9.0%	9.4%	8.0%	9.5%	9.3%	9.5%	9.3%
8	Tax unadjusted	1,840,111	1,842,057	1,917,702	1,914,829	1,973,759	2,003,804	2,017,146	2,019,465
9	Survey adjusted	508,315	528,857	472,301	495,431	456,739	448,163	458,216	477,885
10	Informal	116,826	154,336	112,628	131,354	87,746	85,344	79,889	95,041
11	Inactive	391,489	374,521	359,673	364,077	368,993	362,819	378,327	382,844
12	Survey population adj.	−33%	−29%	−32%	−28%	−33%	−34%	-34%	-33%
13	Informal population adj.	−68%	−58%	−67%	−59%	−72%	−73%	-75%	-71%
14	Tax adj. (months w/income)	1,649,109	1,662,313	1,729,522	1,741,108	1,796,395	1,947,126	-	-
15	Survey adjusted	706,912	715,121	667,823	678,038	644,099	572,252	-	-
16	Informal	315,423	340,600	308,150	313,961	275,106	209,433	-	-
17	Inactive	391,489	374,521	359,673	364,077	368,993	362,819	-	-
18	Survey population adj.	−7%	−4%	−4%	−1%	−6%	−15%	-	-
19	Informal population adj.	−15%	−8%	−9%	−3%	−13%	−33%	-	-

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

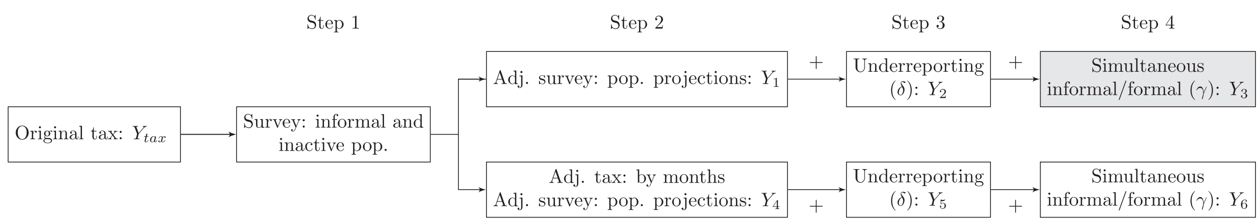


Fig. 1. Overview of Method 1. (*Note.* Own elaboration.)

Table 3
Income control.

	2009	2010	2011	2012	2013	2014	2015	2016	Income
Tax unadjusted	309,532	353,322	412,898	488,090	567,955	659,210	740,858	842,939	Y_{tax}
Survey unadjusted	27,923	30,130	31,795	33,570	36,697	39,513	43,342	48,780	Y_{survey}
% of original tax	9.0%	8.5%	7.7%	6.9%	6.5%	6.0%	5.9%	5.8%	-
Tax unadjusted	309,532	353,322	412,898	488,090	567,955	659,210	740,858	842,939	Y_1
Survey adjusted (total pop.)	8,832	12,624	10,589	13,617	10,138	10,744	11,023	14,167	
% of original tax	2.9%	3.6%	2.6%	2.8%	1.8%	1.6%	1.5%	1.7%	
Tax + informal + under.	348,080	394,894	474,495	555,252	670,657	744,342	846,704	951,598	Y_3
% of original tax	112.5%	111.8%	114.9%	113.8%	118.1%	112.9%	114.3%	112.9%	
Tax adj. (months w/income)	302,344	344,953	403,298	478,309	556,630	640,172	-	-	Y_4
% of original tax	97.7%	97.6%	97.7%	98.0%	98.0%	97.1%	-	-	
Survey adjusted	23,852	27,829	28,974	32,556	31,799	26,383	-	-	
% of original tax	7.7%	7.9%	7.0%	6.7%	5.6%	4.0%	-	-	
Tax adj. + informal + under.	331,677	377,115	447,488	530,169	637,712	720,605			Y_6
% of original tax	107.2%	106.7%	108.4%	108.6%	112.3%	109.3%	-	-	

Note. Own calculation based on tax records (DGI), household surveys (INE) and population projections. Total income in millions of Uruguayan pesos (1 US dollar = 30 Uruguayan pesos).

formal work, or combine formal and informal earnings, a salient feature of developing countries. Thus, to match the actual population total, we need to include an additional reweighting factor to downsize ECH observations (Y_1). To compute this factor, we assume that the inactive population is estimated accurately in ECH and reweight the number of informal workers to match the corresponding total (Table 2, lines 4 and 10). In this case, the added ECH informal income falls to 2 to 3% of DGI income.

In a second variant of Step 2, to account better for inflows and outflows to and from formal work and the joint reception of formal and informal labor earnings we exploit the information (available for 2009–2014 only) on the number of months for which a certain worker has been recorded in the labour earnings database (Y_4). In this way, we are able to weight those individuals with positive labour income in DGI by the number of months they received formal labour income ($\lambda_{it} = \sum_{n=1}^{12} m_{it}$ if $Y_{DGI_{it}} > 0$), in each year. Following this procedure, the population total that we obtain is very close to the actual one and, thus, the residual ECH adjustment factor is negligible (line 18, Table 2). Notice that, as the sum of the earnings reported by the informal population in ECH are very low, the income control falls by approximately 5% and the additional informal income from ECH represents 4% to 8% of DGI total income (Table 3). Unfortunately, since we lack this monthly information for 2015–2016, we discard this option.

In Step 3, we incorporate information from the linked subsample to account for the fact that income from formal occupations reported in ECH is under-captured in tax records. We include this correction because this potential underestimation of the lower tail might yield overestimated inequality measures in tax records.

To overcome this problem, we use an ancillary table containing DGI/ECH harmonized formal labour income ratios for each DGI labour income centile (p) and adjust Y_{tax} as follows (Step 3, income Y_2 and Y_5):

$$\delta_q(Y_{tax}) = Y_{survey}/Y_{tax} \text{ if } Y_{survey} > 0 \text{ and } Y_{tax} > 0$$

Under this adjustment, we inflate DGI total income by 7.9% to 8.7%, depending on the year (Table 3). Fig. 2 shows that in this case, the adjustment mainly affects the centiles in the middle 40% of the distribution. Nonetheless, in the previous steps we did not account for the fact that formal workers might be receiving formal and informal income simultaneously. Hence, to introduce the corresponding correction, we compute the total labour (Y_{survey}) to harmonized labour ECH income ratios by DGI percentile thresholds in ECH micro-data (Step 4). Multiplying the DGI labour earnings by this factor, we obtain an approximation to total labour income ($\gamma_{qit} = Y_{survey_{qit}}/Y_{formal_{qit}}$ if $Y_{formal_{qit}} > 0$). In this case, we add a 4% increase to the original DGI income (Table 3).

As a whole, we are inflating the original DGI income by approximately 15%. It can be noticed that the additional ECH income variables are mainly placed in the lower tail and middle of the income distribution. Table 3 and Figs. 2, 3 and A2.2 summarize the full correction process. Due to space constraints, the table does not include Y_2 and Y_5, but this information is available from the authors on request.

Following the previous steps, we create two adjusted tax income variables (Y_3) and (Y_6). As stated, even re-weighting DGI observations by the number of months in formal work (Y_6) might reflect the dynamics of formal and informal employment more accurately since we lack this information for the whole period, Y_3 is our preferred option:

$$Y_{3_{it}} = \begin{cases} Ysurvey_{it} \text{ if } Ysurvey_{formal} = 0 \\ Ylabour_{tax,it,q} * \gamma_{q,it} * \delta_q + Ypensions_{it} + Ycapital_{it} \text{ if } Ytax_{it} > 0 \end{cases}$$

In this way, we account for income underreporting at formal occupations, informal income in the lower tail and simultaneous reception of formal and informal income. In the next section, we refer to Y_3 as corrected tax income. Fig. 2 shows the contribution of each data source to the composition of this variable by percentile. It can be noticed that the first 17 centiles correspond to the population aged 20 or more with zero income. For all quantiles with positive earnings, income is mostly composed from information from tax records and the corrections are concentrated at the bottom 90%. As expected, pure informal income is concentrated at the bottom 50% of the distribution, whereas income underreporting from formal occupations and simultaneous reception of formal and informal income affect the lower and middle strata.

3.2.3. Robustness checks

As a first robustness check, in the top income shares estimation we also computed alternative income totals for 2012 to 2016 (Method 2) based on SNA information (Y_7). In this case, we use our preferred corrected income variable (Y_3) as the numerator but we use the 80% of the households income account as income control.

In the second place, to assess the sensitivity of our results, we compute the Alvaredo (2011) correction departing from harmonized ECH income and adding the top 1% share calculated for corrected tax income (Y_3).[20] Additionally, we implement the reweighting methodology developed by Blanchet et al. (2018) and create an additional income vector (Y_8).[21] This method identifies a merging threshold at the maximum point at which the survey-tax quantile ratio equalizes the survey-tax densities ratio. To carry out the correction, researchers need to define the minimum percentile at which the tax data are reliable, which we set at p50 due to the considerations presented previously. The endogenous merging point varies around percentiles 50 and 70, depending on the year. Additionally, to check the sensitivity of our results, we imposed merging points at quantiles 50 and 70 and obtain similar results.

4. The recent evolution of primary income inequality in Uruguay

In this section, we analyse income inequality, focusing on the evolution of top income shares and synthetic indices for corrected tax income and harmonized survey income. Unless specified in the text, from this point onwards, corrected tax income refers to pre-tax $Y3$ and harmonized survey income refers to pre-tax individual earnings from formal and informal occupations plus pensions and capital income computed using ECH information.

4.1. Income shares

At first glance, the distribution of corrected tax income did not experience significant modifications throughout the period under analysis (Table 4). The share of the bottom 50% exhibits a mild increase, whereas the middle 40% remained almost unchanged. It is noteworthy that the top 1% holds a larger proportion of the total income than the bottom 50%, although this gap has reduced slightly over the years. A similar comment applies to the middle 40% with respect to the top 10%, although the gap widened in this case and, by 2016, the proportion of the total income accrued by the latter was smaller. In the harmonized survey income, the lower strata increased their participation and, conversely, the top shares decreased. Notice that, in 2009, the income distribution was not very different in the two income variables considered, but diverged over the years.

Fig. 4 depicts the evolution of the top 10%, 1% and 0.1% corrected tax income shares and the corresponding confidence intervals. In line with previous inequality studies for Uruguay, the participation of the higher decile exhibits a statistically significant decline. We are not able to assess whether this point estimate is indicating a reversion of the previous trend. However, the top 1% and 0.1% shares remained almost unchanged in 2009–2013 and exhibit a slight increasing trend since 2014, which is statistically significant in the first case and imprecise in the latter.

Considering the whole period, the point estimate of the top 1% share rose from 13.5% to 14.6%. These values place Uruguay among the countries with the highest concentration at the top among the group of countries for which tax record-based top income estimates are available, only appearing below the remaining Latin American countries, South Africa and the United States (see Atkinson (2007)).

The slight increase in the top income shares in the corrected tax income is in sharp contrast to the declining trends observed in the harmonized survey income (Table 4). The corrected tax income to harmonized survey income ratio of the top 1% shares was 0.88 in 2009, falling to 0.57 in 2016. At the same time, the top 1% thresholds ratio fell from nearly 0.95 to 0.74 (Table A.2). The evolution of these two ratios suggests that the ability of the household survey to capture incomes in the upper tail was eroded in these years. In fact, the 10% thresholds ratio is very close to 1, although it exhibits a mild decline (from 1 to 0.92) throughout the whole period.

[20] According to Alvaredo (2011), the corrected Gini Index can be approximated by: $G = G * (1 - S) + S$, where $G*$ is the Gini Coefficient for the bottom 99% of the distribution, and S is the share held by the top 1%.

[21] To implement this method we resort to the stata code (bfmcorr) provided by the authors.

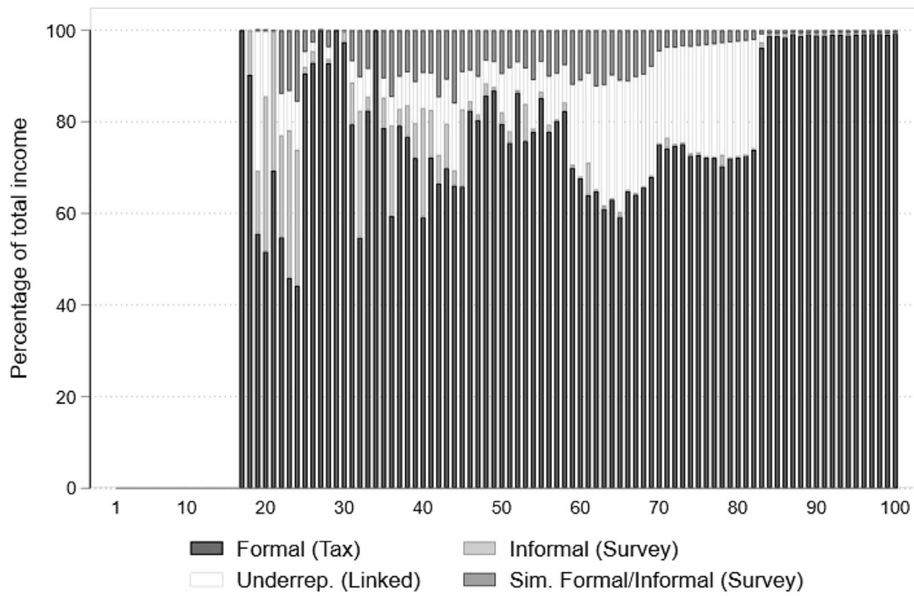


Fig. 2. Income composition by percentile of total income (Y_3). *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

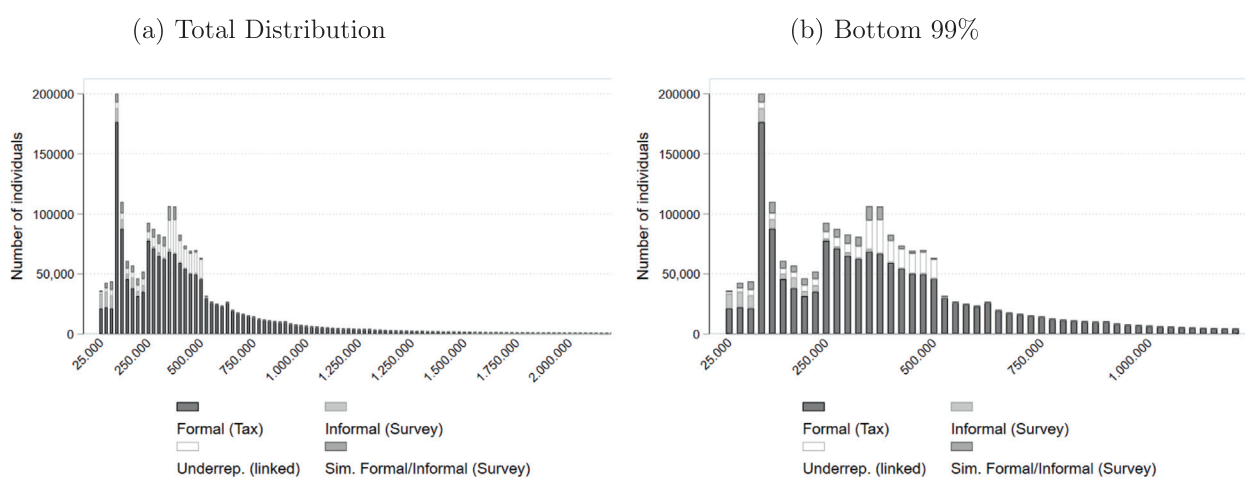


Fig. 3. Composition of the corrected tax income distribution by data source *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

4.2. Synthetic inequality indices

Fig. 5 depicts the synthetic Gini indices computed on the basis of different survey and tax income variables. The longest line corresponds to the survey per capita household income, the income aggregate mostly used in personal income inequality studies. As stated in the introduction, its evolution indicates a sharp decline between 2008 and 2013 and stability thereafter. Although the levels are higher, inequality among income receivers in the survey mimics the path of household income distribution, considering either the full set of income sources or the more restrictive harmonized survey variable used in this study. The 2009–2013 and 2009–2016 Gini and Theil reductions are statistically significant in all cases.[22]

Fig. 5 also depicts the original pure administrative information and the corrected tax income variable. The two lines indicate a mild decline, with the inequality indices converging after 2012 and slightly increasing by 2016. Again, the 2009–2016 and 2009–2013 differences are statistically significant.[23]

Thus, the full set of income variables conveys an inequality reduction from 2009 to 2016, which mainly occurred in the first five years. This finding suggests that the equalization trend is robust to the data base and harmonization criteria, even when the levels and slopes are different. Considering the whole period, the harmonized survey income indicates an 8.6% inequality reduction. Since the corrected tax income only experienced a 2% decrease, the gap has widened in the last years. [24]

[22] See confidence intervals in Table A.3. If we restrict the corrected tax income and harmonized survey income to the subset of observations with positive income, the results are similar in the former case, whereas we find a larger fall (12.6%) in the latter one (Fig. A2.1).

[23] It is noteworthy that these results also hold when considering only the original DGI data without undistributed and non nominative profits imputations. The corresponding tables are available from the authors on request.

[24] Table A.2.9 confirms that these results also hold in the case of Theil's indices.

Table 4
Pre-tax income shares, 2009–2016.

Corrected tax income								
Inc. groups	2009	2010	2011	2012	2013	2014	2015	2016
Bottom 50%	10.8%	11.0%	11.9%	12.2%	13.0%	12.8%	13.2%	12.4%
Middle 40%	45.4%	45.5%	46.1%	45.9%	46.0%	46.1%	46.2%	45.7%
Top 10%	43.8%	43.5%	42.0%	42.0%	41.0%	41.1%	40.6%	41.9%
Top 5%	31.0%	30.8%	29.9%	29.8%	28.9%	29.2%	29.0%	30.3%
Top 1%	13.5%	13.5%	13.5%	13.2%	12.7%	13.2%	13.5%	14.6%
Top 0.1%	4.6%	4.7%	5.0%	4.7%	4.8%	4.8%	5.2%	5.8%
Harmonized survey								
Inc. groups	2009	2010	2011	2012	2013	2014	2015	2016
Bottom 50%	8.7%	9.6%	10.5%	11.1%	11.2%	11.5%	11.3%	11.2%
Middle 40%	47.5%	48.2%	49.4%	51.6%	50.9%	51.0%	50.9%	51.3%
Top 10%	43.9%	42.3%	40.1%	37.3%	37.9%	37.5%	37.8%	37.5%
Top 5%	30.0%	28.5%	26.6%	23.8%	24.6%	24.4%	24.7%	24.4%
Top 1%	11.9%	10.6%	9.6%	7.7%	8.4%	8.4%	8.7%	8.4%
Top 0.1%	3.1%	2.4%	2.1%	1.3%	1.7%	1.7%	1.8%	1.6%

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE). Income thresholds of corrected tax income in Table A.2.7

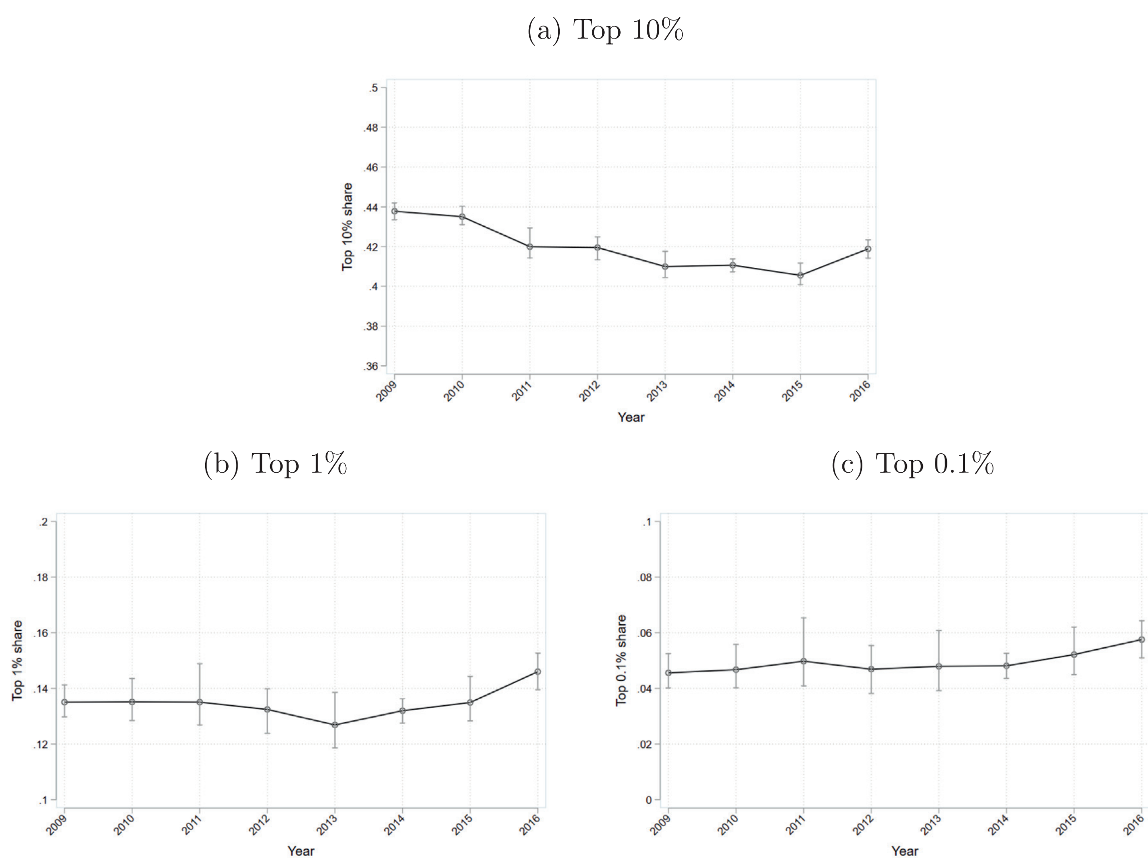


Fig. 4. Pre-tax top income shares, 2009–2016. Corrected tax income. *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE). See the point estimates in Table A.3. Bootstraps with 100 repetitions, with confidence intervals at the 5% level.

4.3. Robustness checks

As mentioned in Section 3.2, to validate our main conclusions, we carry out a set of robustness checks. First, we compute the inequality measures presented in the previous subsections for the seven income variables that we created following Methods 1 and 2. As Fig. A2 shows, the levels vary within a relatively bounded interval, particularly regarding the top 1%. However, the trends resemble the ones presented in the previous subsections: stability or an increase in the top 1% and 0.1% income shares and a statistically significant decline in the Gini and Theil indices. Again, the top 10% share falls steadily until 2015 and rises in 2016.

Second, we take the opposite approach and correct the harmonized ECH data with the tax record information (Fig. A3). In the first place, we implement the correction proposed by Alvaredo (2011). Thus, we compute the Gini coefficient for the bottom 99% with harmonized survey income and carry out the corresponding decomposition using the corrected tax income's (Y_3) top 1% share.

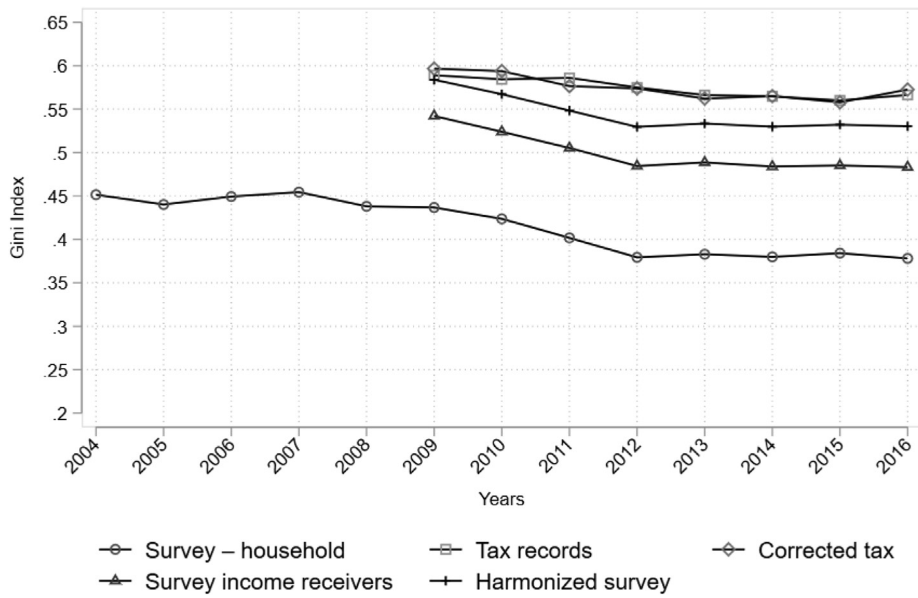


Fig. 5. Inequality trends by income definition and source, pre-tax income Gini index, 2004–2016. *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

As shown in Fig. A2, although the levels are lower, inequality also decreased in this case. If we use the uncorrected tax data (Y_{tax}) instead, we obtain similar results.

In the second place, we implement the reweighting procedure proposed by Blanchet et al. (2018). The endogenous merging point varies over the years, but is always found between the median and the 70th percentile, which implies that the correction starts in a lower quantile than the one usually considered in the empirical implementation of Alvaredo (2011) used here. As Fig. A3 shows, the absolute value of the Gini index is very similar to the one we obtain with Method 1; hence the trend is similar. This conclusion also holds for the different fractiles' levels and trends. In sum, our robustness checks validate the conclusions presented in the previous sections.

5. Reconciling the inequality trends in tax and household survey data

The increasing divergence in the top 1% thresholds in harmonized survey and the corrected tax income might be consistent with the larger reduction in inequality in the former case vis á vis the latter. To dig further into these differences, we first present the Gini and Theil indices decompositions by income subgroups, to isolate the movements and the contribution to inequality of the top 1%. After that, we analyse the evolution of the densities and inequality indices at the top, singling out the intervals in which the tax and survey overlap and those that are beyond the survey maximum. Finally, we compare the composition of income by source (pensions, labour earnings and capital income) in the harmonized survey and corrected tax income.

5.1. Inequality decompositions by income groups

We decompose the Gini and Theil indices by income groups, considering the bottom 99% and the top 1% (Table 5 and Table A.2.9).[25] In both in corrected tax income (Y_3) and the original tax income variable (Y_{tax}), the proportion of between groups inequality remained steady and grew slightly in the last two years, indicating an increased distance in the two groups' average income. Meanwhile, the harmonized survey income exhibits the opposite pattern, with a substantial decline in the between group inequality fraction over the years. The results for the Theil's index decomposition are similar, with an slightly increase in the between group fraction both in pure tax and in Y_3 income (from 30% to 40% for the latter).

The last two rows in the panels depicted in Tables 5 and A.2.9 present the inequality indices for the two income subgroups. The two DGI based income variables indicate a sharp contrast between the equalizing trend of the bottom 99% (−6%) and increased concentration at the top 1% (20%).[26] Nevertheless, in harmonized survey micro-data the two income groups experienced a substantial inequality decline. Moreover, the reduction is larger for the top 1% (11% and 35%, respectively).[27] The two subgroups present the same patterns as the Theil index decompositions.

These results strengthen the hypothesis that the equalizing trends observed in the synthetic indices in the harmonized survey and tax based variables stem from very different movements throughout the income distribution. The between group inequality shares indicate that the subgroup's average income diverged in the tax records and converged in harmonized survey income. This finding is consistent with the falling survey/tax top 1% threshold ratio presented in Table A.2. At the same time, the mild inequality reduction observed in the tax data results from an offsetting fall in the concentration of the bottom 99% against the increased inequality at the top. Conversely, in the harmonized survey income, inequality fell in all the income groups, although the reduction was considerably larger at the top. It is worth noticing that even when the fall was steeper (11% versus 7%), inequality trends for the lower 99% were relatively similar in the harmonized survey income and in the tax data.

[25] Since we are using income quantiles, we can obtain exact population subgroups decompositions for the Gini and Theil indices (Cowell, 2011).

[26] These results also hold for all the DGI income variants, either considering the original uncorrected tax data (without adding bank deposits, non nominative profits and undistributed profits), or in the case of the remaining corrected income variables.

[27] The results are similar for the lower 99% in the three subgroups.

Table 5
Pre-tax Inequality decomposition between two income groups, 2009–2016.

	2009	2010	2011	2012	2013	2014	2015	2016
				Corrected tax income				
Gini index	0.597	0.594	0.577	0.574	0.562	0.565	0.558	0.573
% between	21.0%	21.1%	21.7%	21.3%	20.8%	21.6%	22.4%	23.8%
% within	79.0%	78.9%	78.3%	78.7%	79.2%	78.4%	77.6%	76.2%
% overlap	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Gini bottom 99	0.550	0.547	0.527	0.525	0.515	0.515	0.505	0.516
Gini top 1	0.347	0.356	0.380	0.365	0.390	0.380	0.402	0.417
				Harmonized survey				
Gini index	0.584	0.567	0.548	0.530	0.533	0.530	0.532	0.530
% between	17.9%	16.3%	15.0%	11.8%	13.4%	13.3%	13.9%	13.5%
% within	82.1%	83.7%	85.0%	88.2%	86.6%	86.7%	86.1%	86.5%
% overlap	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Gini bottom 99	0.547	0.535	0.519	0.508	0.508	0.505	0.505	0.505
Gini top 1	0.261	0.221	0.205	0.133	0.185	0.175	0.192	0.177
				Tax records				
Gini index	0.589	0.584	0.586	0.575	0.566	0.565	0.560	0.566
% between	17.5%	15.8%	14.7%	11.7%	13.1%	13.0%	13.6%	13.1%
% within	82.5%	84.2%	85.3%	88.3%	86.9%	87.0%	86.4%	86.9%
% overlap	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Gini bottom 99	0.540	0.535	0.533	0.523	0.513	0.511	0.503	0.505
Gini top 1	0.355	0.364	0.389	0.373	0.399	0.385	0.408	0.422

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE). The table is divided in three panels, presenting the corrected income in harmonized surveys and tax records respectively. By construction, both micro-data bases refer to the same individuals and the same incomes (pre-tax and total formal income). In each panel, the Gini index is decomposed into *between* and *within* components, among the groups defined (bottom 99% and top 1%). Within group inequality is shown in the last two rows of each panel.

5.2. Movements in the upper tail of the income distribution

In the preceding sections, the top 1% thresholds were endogenously defined for each data source. However, as shown in the previous subsections, the harmonized survey/corrected tax income thresholds ratio decreased monotonically. Hence, the top 1% share of corrected tax income is defined with an increasingly larger absolute income value than the one in the harmonized survey. To test whether the conflicting trends in relative income and within group inequality at the top might result from these differences, we compute the proportion of observations beyond the harmonized survey top 1% threshold and inequality measures in corrected tax income, separately considering: (1) observations with income above the 1% threshold in the harmonized survey and below the survey's maximum; and (2) observations with income above survey's maximum (see Fig. A4).

In 2009 and 2016 the proportion of corrected tax income observations belonging to each group (group 1: 1.3% and 2.0%; group 2: 0.15% and 0.25%) indicates that most of the observations used to compute the top 1% lie in the common support. Thus, the problem is not only reaching the rich who are above the survey maximum but representing correctly those individuals located in the common support. Both subgroups, but particularly group 1, present an increasing share, again reflecting the divergence between the two data sources. Lowering the threshold (beyond the survey threshold) to compute the Gini index of the corrected tax income does not affect the inequality trends at the top of corrected tax income.

Fig A.2.3 (panel a) depicts kernel density functions for those observations pertaining to the top 2% of the corrected tax income in selected years. The vertical red line represents the maximum of the harmonized survey income (or the limit between group 1 and group 2). Two features are noteworthy: an inequality increase in group 1 and an augmented fraction of income received by the top 1% and 2%. Thus, the observed differences in the top incomes shares and top 1% inequality indices are noticeable in the common support and are not only driven by the corrected tax income capturing richer individuals but seems to result from an increasingly lowered density in the common support. Notice that, in both groups, the gap increases in 2012, close to the end of the inequality reduction period.

To conclude, we present a brief parametric analysis of the evolution of inequality at the top-end, based on the Pareto I distribution.[28] Fig. 6 shows the survival function (Cowell, 2011; Atkinson, Casarico, & Voitchovsky, 2018). First, in all cases the survival function is concave at the top, indicating that the Pareto parameter (α) decreases with income. Atkinson et al. (2018) labeled this shape as "regal" to indicate the large distances between the different observations at the top, opposing it to the "baronial" pattern in which the distances among observations at the top are smaller. Second, the slope of the 2016 survival function is less steep than those for 2009 and 2013, indicating an inequality increase in the upper tail throughout the years. In turn, the evolution of the beta clearly shows an increasing differentiation of incomes at the top-end, despite the income threshold (see panel b) of Fig. 6. 2012–2013 again seems to be a watershed regarding inequality trends. Third, the β coefficients ($\alpha/\alpha - 1$) indicate an increasing differentiation of incomes at the top, despite the threshold.

These findings suggest that differences in inequality trends might result from diverging concentration patterns at the upper tail in ECH and DGI data. Considering the short period under analysis, a 32% reduction in the harmonized survey income Gini coefficient for the top 1% seems extremely high compared with previous evidence on inequality reduction trends at the top. On the side of administrative data, two main features might create an artificial inequality increase: reduced informality with the subsequent entry of low-salaried workers in the data-base and a greater ability of the tax authority to enforce tax-payments. Furthermore, the evolution of inequality in the bottom 50% rules out the possibility of corrected tax income trends being driven by the formalization pro-

[28] The purpose of this exercise is not to analyse in depth the parametric function that best fits the Uruguayan data, but to inspect briefly the shape of the upper tail, that is, the income differences at the top-end of the distribution. As Jenkins (2017) and Charpentier and Flachaire (2019) show, Pareto I estimates are very sensitive to the threshold. To overcome this potential draw-back, we also consider the three thresholds analysed previously (the top 1% in the harmonized survey and the corrected tax income (Y_3) respectively, and the maximum at ECH) and the results are similar.

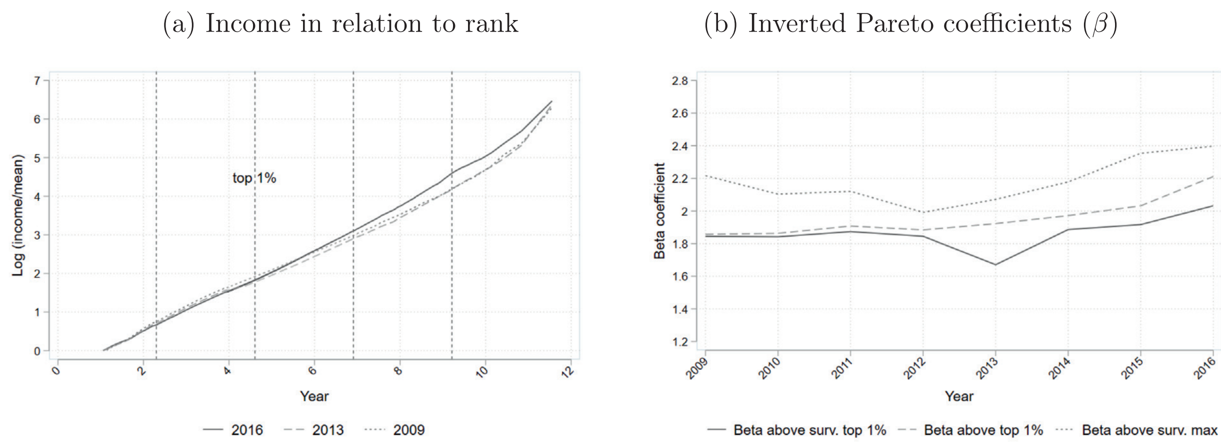


Fig. 6. Inequality at the top tail of corrected tax income, 2009–2016. *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE). In panel a, the y axis depicts the log of income as a proportion of the mean income, while the x axis depicts the log of $\frac{1}{S}$, with S being the survival function. Vertical lines respectively represent top 10, 1, 0.1 and 0.01% thresholds. All the incomes are annual and at 2016 prices. In panel b, the top 1% threshold refers to the total income distribution in corrected DGI data.

cess. Although the available data do not allow us to solve this puzzle, in the next subsection we dig a little further into these differences, focusing on the capital income share in both distributions.

6. Income sources and characteristics at the top

6.1. The growing share of capital income

The previous section findings suggest that the differences in inequality trends among administrative and survey data result from divergent trends at the top of the income distribution. Thus, the ability of household surveys and administrative data to capture the different income sources can contribute to shedding light on these discrepancies, particularly, if during this period, capital income earnings increased as this income source is associated with higher underreporting rates in ECH. To explore this point further, we first analyse the composition of income by source (Figs. 7 and A6) and present the Lerman and Yitzhaki (1985) inequality decomposition by income source.

These results uncover the expected pattern: labour earnings account for around 75% of the total income in harmonized survey income and fall to 66% in corrected tax income. Since the share of pensions is similar in the two data-sources, the whole difference is due to the capital income share, which is around three or four times larger at the tax records database and increases throughout the period, whereas it falls in household survey data. Again, this pattern is consistent with the different trends in the top incomes shares observed in the two data-sets. The available SNA data on the capital income share in the households account show a slight increase from 10.9% in 2012 to 12.8% in 2016. These figures are closer to the ones computed using the corrected tax income, ruling out the possibility that the corrected tax income trajectory has been lead by the increased capacity of the tax authority to reach the rich.

In the corrected tax income estimations there is a substantial increase in the participation of capital income at the top throughout the whole period, which is not mirrored in the harmonized survey income. In fact, our estimations indicate that whereas the top 1% receives 37% of total capital income in the harmonized survey, this figure rises to 62% in the corrected tax income. The increasing share of capital income at the top might be the driving force explaining the divergent trends at the top. It is worth noticing that in 2016, the capital income and mixed income equalize the share of labour earnings for the top 1% and surpassed it for the top 0.1% at corrected tax income.[29]

Table A.5 presents the results of the Gini coefficient decomposition by income source for the corrected tax income and the harmonized survey income. As expected, capital income and mixed income are the most unequally distributed income components, followed by pensions (probably related to the number of individuals who are not pensioners). In both cases, labour earnings make the greatest contribution to overall inequality, with a larger share in harmonized survey income. In spite of its diminishing share in ECH, the contribution of capital income to overall inequality increased over the years, in both data sources. Again, the decomposition yields to different patterns in the two data sources, with a larger contribution of labour income to inequality in the ECH data. Conversely, in the corrected DGI income, the contribution of capital income and pensions is substantially larger.

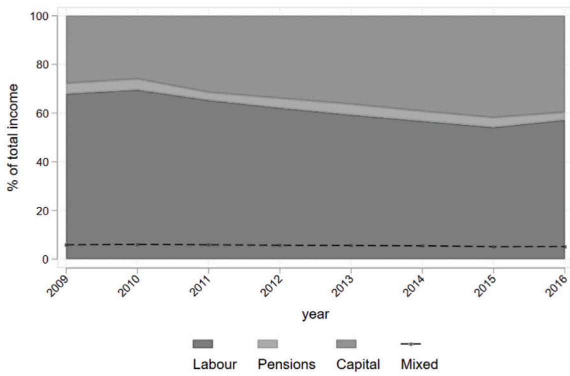
To investigate further the interplay between the evolution of the relative participation of the different income sources and the concentration at the top of the corrected tax income distribution, we decompose the evolution of the top 1% income share in two factors (Boschini et al. (2020)): the total share of the different income sources and the variation in the share of the different income sources held by the top 1%. We group the share of labour income and pensions (q) on one side, and the capital share ($1-q$) on the other. The share of the top 1% in the joint labour earnings and pensions distribution is a and b is the corresponding top 1% share in the total capital income.

$$
\begin{aligned}
\Delta s &= s_{t+1} - s_t \\
&= (a_{t+1} - a_t)q_t + (b_{t+1} - b_t)(1 - q_t) + (a_{t+1} - b_{t+1})(q_{t+1} - q_t)
\end{aligned}
$$

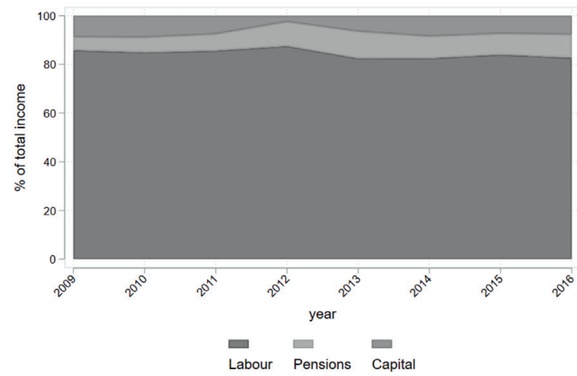
The first term represents the contribution from changes in non-capital income, the second one reflects the contribution of changes on capital income, and the third one corresponds to the contribution of the changes between sources.

As it can be noticed from Table 6, the 1.1% percentage points increase in the top 1% share results from a 41% increase in $1-q$ coupled with a 10% increase in b that is not outweighed by the equalizing trend in the distribution of labour and pensions earnings. Meanwhile, in the harmonized survey income $1-q$ was constant and exhibits a smaller share, and the 46% reduction of the top

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



(a) Corrected tax income - Top 1%



(b) Harmonized survey income - Top 1%

Fig. 7. Pre-tax income composition by source, 2009–2016. *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE). In tax records, mixed incomes are depicted as a share of the labour income for comparison purposes.

Table 6
Inequality decomposition by income source, 2009–2016. Pre-tax corrected income and harmonized survey income.

Panel A: Capital and non-capital incomes shares by source (Y3 and harmonized survey)					
			Corrected tax income		
	Top 1% share	Labor + pensions (q)	Capital (1-q)	Labor + pensions top 1 (a)	Capital top 1 (b)
2009	13.5%	94.1%	5.9%	10.4%	63.1%
2016	14.6%	91.7%	8.3%	9.6%	70.1%
			Hamonized survey income		
	Top 1% share	Labor + pensions (q)	Capital (1-q)	Labor + pensions top 1 (a)	Capital top 1 (b)
2009	11.9%	96.1%	4.0%	13.8%	31.9%
2016	8.4%	96.2%	3.8%	10.1%	21.2%
Panel B: Contribution of each source to the change in the top 1% share					
			Corrected tax income		
		Top 1%	Labor + pension	Capital	Change between sources
Change 2009–2016		1.1%	−0.7%	0.4%	1.4%
Contribution to change		100%	−66.3%	37.7%	128.7%
			Hamonized survey income		
		Top 1%	Labor + pension	Capital	Change between sources
Change 2009–2016		−4.0%	−3.5%	−0.4%	0.0%
Contribution to change		100%	89.0%	10.6%	0.4%

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

1% share (4 percentage points) results from a 50.5% reduction of its share in capital income and a 41.6% decrease in labor income. Notice that the top 1% share in labour income declined in the corrected tax income and harmonized survey, although the reduction was larger in the latter case. In sum, the diverging trends of the top 1% share in survey and tax data are closely related to the evolution of capital income inequality, which in the tax corrected income seems to outweigh the equalizing trend of labour income and pensions.

In their study on the United States, Kopczuk and Zwick (2020) pointed out that correctly identifying the different income sources at the top of the income distribution is not an easy task. Personal income taxation as well as the mechanisms used by firms and, particularly, big corporations to set payments to managerial personnel (partially driven by the specific features of the income tax schedule) clearly shape the definition of income sources. At the same time, in case if it is possible to observe it, it will be necessary to determine whether the annual distribution of profits to liberal professionals can be considered to be capital income. Thus, the limits between labor and capital income can be an unintended result of the personal income tax schedule and corporate decisions.

It is worth pointing out that personal income taxation did not offset the increased share of capital income and the top fractiles. Although personal income taxation in Uruguay is progressive, it has modest redistributive effects. It approximately reduces the top 10% and 1% shares by 12–14% and 5–6% (2.5 and 2 percentage points respectively), with a subsequent increase in the middle 40% and the bottom 50% (Table A.4). In addition, the IRPF became less redistributive in the period under analysis. This effect is probably related to the dual nature of the Uruguayan taxation scheme, coupled with the increased share of entrepreneurial profits and dividends at the top; these are taxed at a lower rate than the remaining capital income sources (7% versus 12%, Table A.2.1). As a result, tax rates effectively paid by the top 1% are lower than the ones for lower neighbouring fractiles and the same pattern holds for the top 0.5 and 0.1% (Fig. A8). This regressive capital income taxation scheme is reflected in the 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% (see Fig. A8).

To conclude this subsection, we assess the share of the different capital income concepts for the corrected tax income quantiles. As previously shown, capital income is disproportionately concentrated at the top of the income distribution.[30] Property rents exhibit

[30] Recall that since individuals own occupied housing is not included in the Uruguayan personal income tax scheme, our results might be biased as we exclude the most widespread form of capital income from our calculations.

a larger share for centiles 90–99, whereas dividends account for around 45% of the capital income at the top-end (see Fig. A7). Dividends are clearly the most unequally distributed capital income subcomponent. The predominance of capital income and, specifically, dividends in 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 predominate (Alvaredo & Londoño Velez, 2014).

In subsection 5.2 we have shown that there is an increasingly lowered density at the common support in ECH and a 32% fall in the concentration of the top 1% in the survey. The reduced capacity of household surveys to capture high incomes is consistent with the fact that the increase at the top is mainly caused by capital income growing to a larger extent than labour income. In fact, our decomposition exercises indicates that the increased top 1% share is explained by capital income inequality and that personal income taxation does not morigerate this evolution. As mentioned at the beginning of this subsection, the SNA information indicates that the capital income share rose from 10.9% in 2012 to 12.8% in 2016. The information presented in this section shows that in ECH, the capital share remained almost steady and exhibited a considerably lower share (4.7 to 5.1%), whereas in Y_3 it grew from 10 to 15.3%, which is consistent with SNA information. At the same time, from Table A.2.8, it can be noticed that the participation of dividends within capital income rose from 13.4 to 29.6%. These findings suggest that the evolution of dividends played a key role in the growth of the capital income share, an income concept considerably undercaptured in household surveys.

6.2. Top income holders: a brief characterization

In this section we examine the main characteristics of the individuals belonging to the different income fractiles, focusing on the top of the corrected tax income distribution. Since in the previous section we show that the upper tail is misrepresented in the harmonized survey income, this exercise can only be carried out with tax records information.[31] Furthermore, we exploit the matched firm-worker/owner data-base. We present evidence on gender differentials and carry out a multivariate analysis.

In line with previous studies on wage differentials, our estimations show that the proportion of women in the total and labour income decreases with the quantile (Fig. 8, panel a), ranging from more than 50% below the median to 25% at the highest percentile. The estimations reported by Atkinson et al. (2018) for eight high income countries yielded to very similar results. Due to differences in life expectancy patterns coupled with the wide coverage of the Uruguayan pensions system, the presence of women is larger among pensioners. Even though the differences are smaller in this case, the presence of women declines with income (60% and 40% respectively). Conversely, women are severely underrepresented among liberal professionals and capital income receivers. Considering the distribution of income instead (panel b), the results are very similar, although women's share is even smaller in most cases, probably reflecting the earnings gap within these categories. In sum, capital income and earnings from liberal professionals mirror and widen the gender gap documented for labor income in previous studies on Uruguay (Amarante, Arim, and Yapor, 2016; CEPAL, 2020; Espino, Isabella, Leites, and Machado, 2017; Domínguez-Amorós, Batthyány, and Scavino, 2021).

In their study covering five decades in Sweden, Boschini et al., 2020 reported that the participation of women evolved from 6% to 19% in the top 1% and from 5 to 15% in the top 0.1%. This trend was lead by their increased participation at the top of the labour earnings distribution. However, men increased their share at the top of the capital income distribution. Despite the short time span considered in this article, a similar pattern can be identified here for labour earnings and pensions (see Fig. A5, panel a). Meanwhile, the participation of women in capital income as a whole remained relatively constant, with an increase in housing rents and stability in business income (Fig. A5, panel b).

To further deepen into the characteristics of top income earners, we estimate two different probit models on the probability of being in the top 1% against the remaining 99% or the top 10%, for the total population and opening by gender (marginal effects can be checked in Table A.8).[32] Among the covariables, we include individual characteristics (sex and age), type of employment (liberal professional, salaried worker, self-employed, and multi-employment), a set of binary variables reflecting the different income sources received by the individual (pensions, labour earnings, capital income, dividends, housing rents and other capital income) and firms characteristics (size, type of business and industry). Industries are opened at the section level (ISIC, rev. 4).[33] Additionally, as our descriptive analysis indicates that workers at financial activities (K) and human health services (Q) are over-represented at the top of the labor earnings distribution, we further disaggregate these divisions.[34] Regarding section Q, we incorporate three binary variables reflecting the classes that are overrepresented at the top 1%: hospital activities (8610), medical and mental activities (8620) and other human health activities (8690). In the case of section K, we include the three financial activities divisions (64, 65 and 66).

Probit estimates for 2016 show that, relative to the bottom 99%, individuals belonging to the top 1% are more likely to be men and liberal professionals. At the same time, they exhibit a higher probability of receiving capital income, dividends and, to a lesser extent, labor income. Conversely, pensioners are less likely to belong to this group. There are also gender differences in the marginal effect of receiving labor income, which is positive but very low for the total population and men, while it is not statistically significant in the case of women.

Regarding the estimates within the top 10%, it is worth pointing out that the same differences hold but, again in line with the descriptive findings, the gender gap is thirteen times larger than the one corresponding to the top 1% versus the whole population. Differences by income source also hold within the top 10%, but in this case, the marginal effects of receiving dividends are considerably larger than the capital income ones. Liberal professionals exhibit a high probability of reaching the top 1% relative to remaining in the top 10%. In contrast, the marginal effects of receiving labor earnings is negative for the average and women, while they turn to be not statistically significant in the case of men.

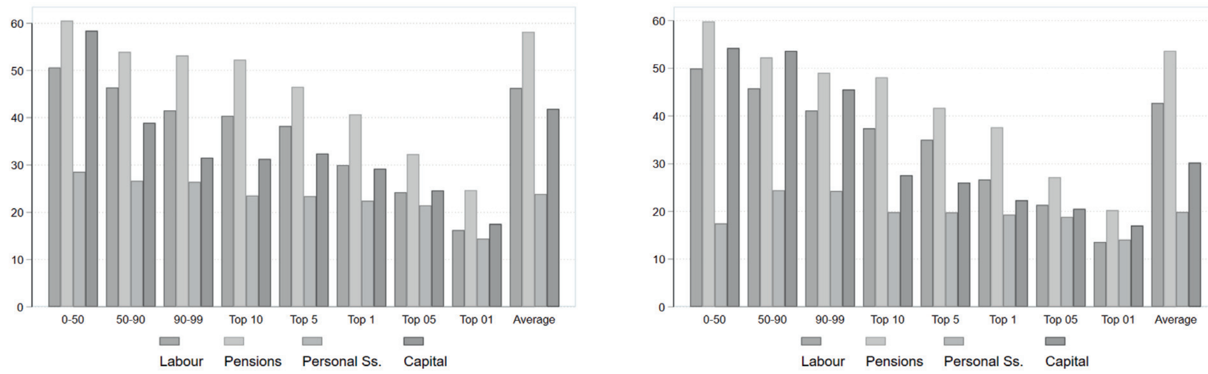
With respect to the differences by industry, higher income positions are associated to the manufacturing, financial, wholesale and retail, public administration, health activities and financial services sectors. These results hold both for men and women. The first three

[31] The data used in this section are representative of formal occupations, pensioners and capital owners, leaving aside informal workers, who represent approximately 20% of the Uruguayan labour force and are by large self-employed. Unfortunately social security and tax data lack information on schooling

[32] Additional estimations restricted to individuals with positive labor earnings are available on request to the authors.

[33] We grouped agriculture, forestry and fishing, and mining and quarrying (A and B, the omitted category); transportation and communications (H and J); and other services activities, activities of households as employers and activities of extraterritorial organizations (S,T and U).

[34] Table A.7 shows that almost half of the top 1% of the labour earnings distribution is concentrated in three sectors: liberal professional and health services (29%), financial and business services (11.9%) and other liberal professional services and public administration (6.2%). In sharp contrast, no sector predominates in the capital income distribution. The share of the health sector decreases to 6% and the financial sector shrinks considerably to 3.6%, which can be explained by the significant share of the public sector and foreign firms in the banking sector.



(a) Proportion of female income receivers (b) Proportion of pre-tax income held by women

Fig. 8. Participation of women in total income and receivers (by income source and income group, 2016). *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

columns of Table A.8, indicate that the magnitudes of the marginal effects of the health related activities, and particularly hospitals, are considerably larger than the financial sector ones. The last three columns of the table (differentiation within the top 10%), exhibit considerably larger marginal effects for the health services classes (4 times for the total), particularly in the case of hospitals. In this case, the differences with the financial services classes marginal effects are substantial. These findings are consistent with the descriptive information presented in Table A.7 for 2016, that shows that approximately 1 out of 4 top income holders receiving labour income are occupied in health services, whereas this figure declines to 8% for the financial sector.

In their characterization of Canada's top 1% earners, based on Census data for a larger time span (1981 and 2006), Lemieux & Riddell (2015) identified the leading force under the increasing share of the top 1% as executives compensations and financial and business services, whereas the medical sector has lost relative relevance. It is hard to determine whether the different pattern found in this study is an Uruguayan feature or whether it holds in other Latin American countries, since previous top incomes studies for Argentina, Brazil, Chile and Colombia do not provide similar disaggregations.

The set of dummy variables reflecting type of business shows that individuals that work or withdraw dividends from corporations receive larger earnings, and these effects substantially increase when observing differences within the top 10%. Approximately 60% of the individuals at the top 1% are occupied in corporations. Being a public employee is also positively associated to belonging to the top 1% versus the rest, but when we compare within the top 10%, these coefficients fall and lose statistical significance.[35]

The comparison of the estimations obtained for 2009, 2013 and 2016 (Table A.2.10), indicates a that the occupations associated to health activities increased their probability of being a the top of the income distribution and widened their distance with the classes pertaining to the financial sector. At the same time, the association among being a liberal professional or receiving dividends and belonging to the top 1% increased, and the same happened (but at lower absolute levels) with property income. This pattern is in sharp contrast with the coefficients reflecting the reception of labour income, whose magnitude fell and even changed sign in 2016.

7. Final remarks

As in most Latin American countries, previous studies based on household survey micro-data have shown that Uruguay experienced a substantial decrease in inequality in the period 2008–2013, which resulted from high economic growth rates that fostered the demand for unskilled workers, coupled with a package of reforms that included the restoration of centralized wage-setting mechanisms, the inception of a progressive personal income taxation scheme and the expansion of non contributory cash transfers (Amarante et al., 2014). To determine whether this trend resulted from household surveys draw-backs in capturing the upper tail of the income distribution, in this article we analysed primary income inequality among the adult population aged 20 and above, creating a corrected tax records income variable and comparing it with harmonized household survey micro-data. Differently from previous studies for other Latin American countries, we had access to a unique data-set that covers a substantial fraction of the adult population; this allowed us to include informal income and correct underreporting from formal occupations in the the personal income tax records distribution, to compute both synthetic indices and top income shares, and to investigate the characteristics of the top income holders.

We found that, in both databases, synthetic indices experienced a statistically significant reduction (although milder for corrected tax income) in 2009–2013, which remained unchanged afterwards. The top 10% share in our corrected tax income variable mimicked this evolution, although in 2016 experienced a statistically significant increase. It is still soon to understand whether this is reflecting a new trend or it is a point variation. At the same time, the income share accrued by the top 1% was stable and grew slightly in our corrected tax micro-data income variable in the last years, whereas it fell significantly in the harmonized household survey income throughout the whole period. We carried out a wide set of robustness checks that strengthened these findings. Our study contributes further evidence to that already provided by Alvaredo and Londoño Velez, 2014, (Flores et al., 2019) and Morgan (2017) for Colombia, Chile and Brazil on the divergence

[35] We also estimated a set of quantile regressions valuated at the median, the top 10, 1 and 0.1% that are available on request to the authors. The results are consistent with the ones obtained from the probit models estimations. The magnitudes of the coefficients associated to receiving capital income and its components substantially increase with the quantile. Conversely, receiving labor earnings is more relevant in the median and the magnitudes of the coefficients are considerably lowered at top points of the distribution. Again, being a pensioner yields a negative sign along all the quantiles considered. The patterns regarding industry and business type are similar to the ones obtained in the probit estimations.

between household survey inequality measures and top income shares based on tax data.

Whereas the inequality indices within the bottom 99% present a declining trend in both data-sets, the different trajectories of the top 1% explain the diverging trend in top income shares. In the harmonized household survey data, inequality within the the top 1% experienced a 35% reduction that contributed substantially to the overall equalization observed in 2009–2013. Meanwhile, for the corrected tax income, the top 1% experienced an increasing concentration trend over the years, which we document in several ways. After 2012, the inequality reduction at the bottom 99% could not offset the concentration at the top.

The significant inequality reduction experienced by the harmonized household survey income in the top 1% and the income redistribution observed for the bottom 50% of the tax-records distribution convey the idea that these differences are driven by the eroded ability of ECH to capture the upper tail of the distribution, rather than by the formalization process or an improved capacity of the tax authorities to reach the rich. Moreover, the increased inequality at the tax records top-end is mainly explained by the increasing share of capital income, which can be associated with a higher misreporting in household survey data. Our decomposition exercise shows that increased participation of capital income, along with the augmented inequality within this income source and the rise in the participation of dividends, accounts for the increase in the proportion of income held by the top 1%. These findings also highlight the relevance of monitoring and renewing the ways in which household surveys gather information and the need to articulate this information with other valuable datasources, such as information from tax records.

Our study suggests that the recent fall in inequality in Uruguay was driven by equalization at the bottom and middle of the distribution, whereas the top remained unchanged. The meagre effect of personal income taxation provide further evidence on the weaknesses of redistributive policies and dual tax schemes in reaching the top-end of the distribution. The Uruguayan effective rates are relatively low when compared with those of the OECD countries, although they are double the available ones for Colombia (Alvaredo & Londoño Velez, 2014).

We also document that the Uruguayan top income holders are mainly male and obtain a significant proportion of their earnings from capital income and, specifically, dividends. Different from the available information for developed countries, labour earnings at the top are highly concentrated in the health and professional services' sectors. Broader issues such as analysing the socio-economic stratification on the basis of a wider scope of variables need to be investigated further.

Although our results indicate that the dividends obtained by top income holders are generated in a wide set of industries, it is worth mentioning that this empirical exercise assessed national income and, thus considered approximately 15% to 33% of the total amount of dividends generated in Uruguay. Consequently it lacked information on non resident owners of domestic assets. The consideration of dividends that are remitted abroad might lead to a very different characterization of the top of the distribution. A similar point holds for income obtained abroad by Uruguayan residents, as the recent literature on tax havens has suggested (Zucman, 2013; Zucman, 2014). These specific features of small open economies need to be studied in further research.

The apparent contradiction between the stability of the top income shares and the evolution of the Gini and Theil indices in our tax based income variables calls into discussion several issues related to the kind of inequality reduction is sought. Furthermore, it contributes to the appraisal of the relationship between economic growth and redistribution as well as the extent of the equalizing effect and limitations of the menu of redistributive policies launched in Latin America and in Uruguay in the last two decades. As Lemieux & Riddell, 2015 argue, most of these interventions affect the low, middle and upper-middle sectors, rather than the top incomes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

We are grateful to Gustavo González, former coordinator of Asesoría Económica at Direcci on 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 Gomez Sabaini, Rosa Grosskoff, Juan Pablo Jiménez, Nora Lustig, Jorge Onrubia, Nelson Noya, Darío Rossignolo, Gabriela Pacheco, Alberto Sayagues and participants at Taller Desigualdad y Tributacion a los Altos Ingresos (CEF-ECLAR AECID); Fiscal Policy and Income Redistribution in Latin America Workshop, CEQ, Tulane University; HLEG OECD Workshop (Berlin); ECINEQ; Instituto de Economia weekly seminar, and two anonymous reviewers 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.

Appendix A

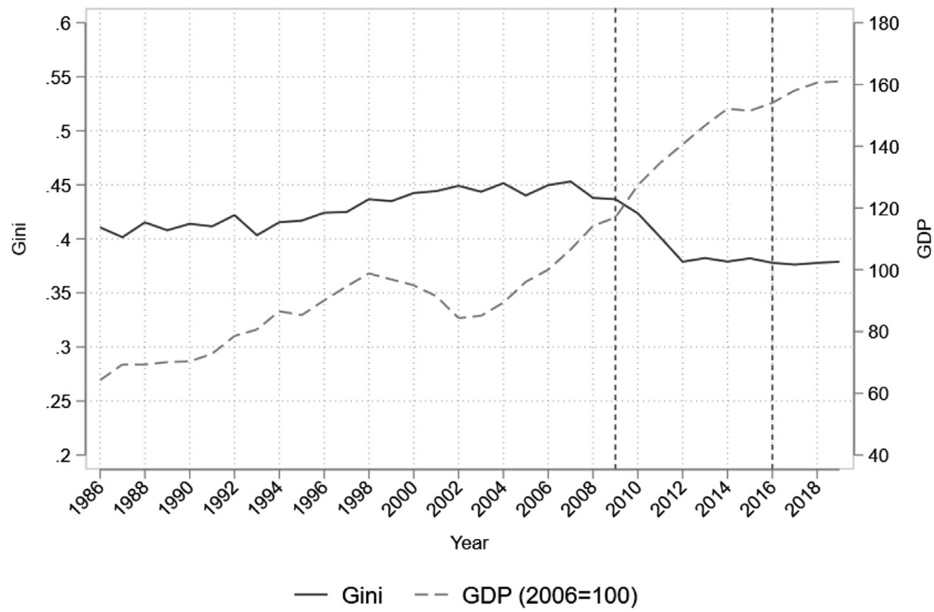


Fig. A1. Inequality trends in Uruguay. Per capita household income. 1986–2019. *Note.* Own calculations based on ECH micro-data and System of National Accounts (from Uruguay's Central Bank, *BCU*). Per-capita household income includes all cash and in-kind income sources and rental imputed income. Incomes adjusted at December 2006, based on consumer prices index. For a complete description of the household survey, see Section 3. Vertical lines indicate the period under analysis .in this study.

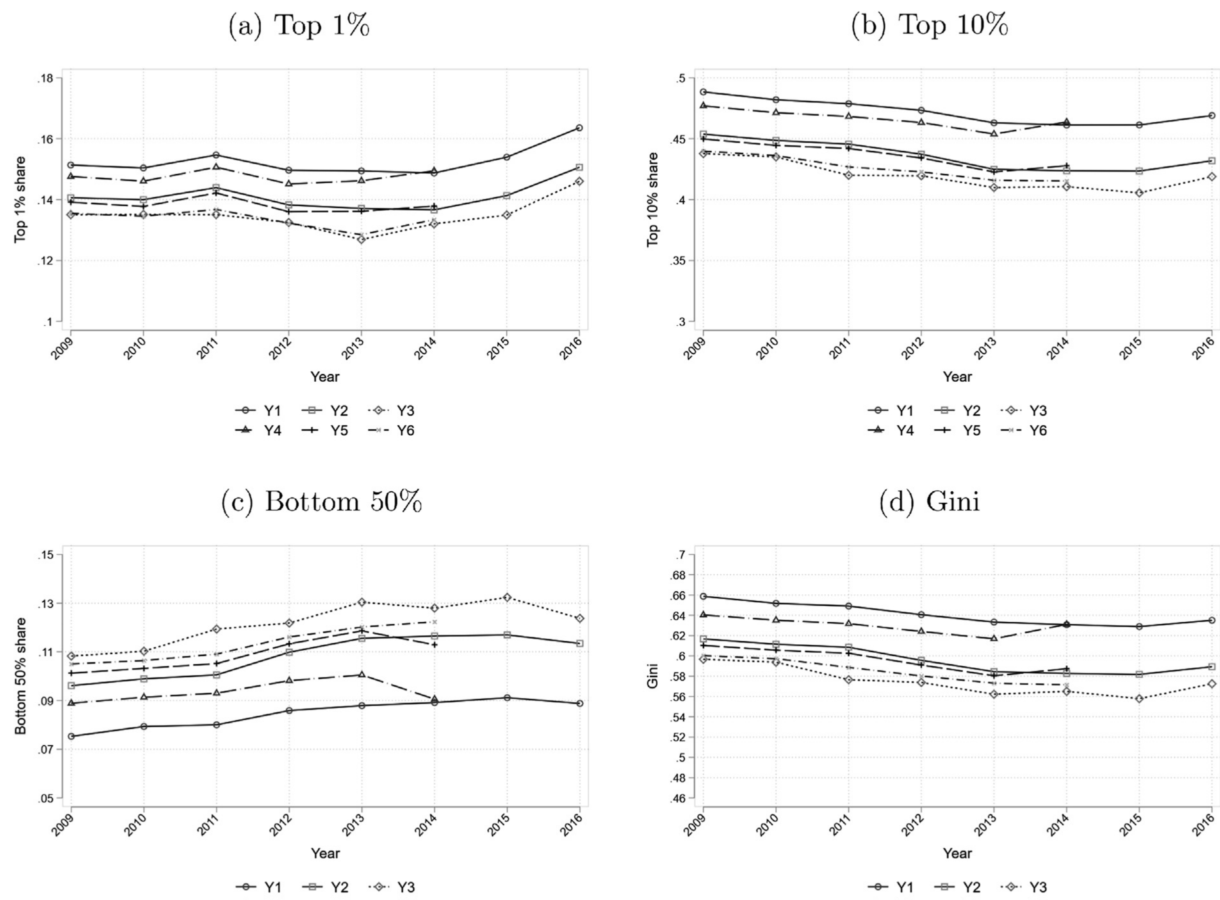


Fig. A2. Pre-tax top income shares, 2009–2016. Method 1. Alternative income variables. *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

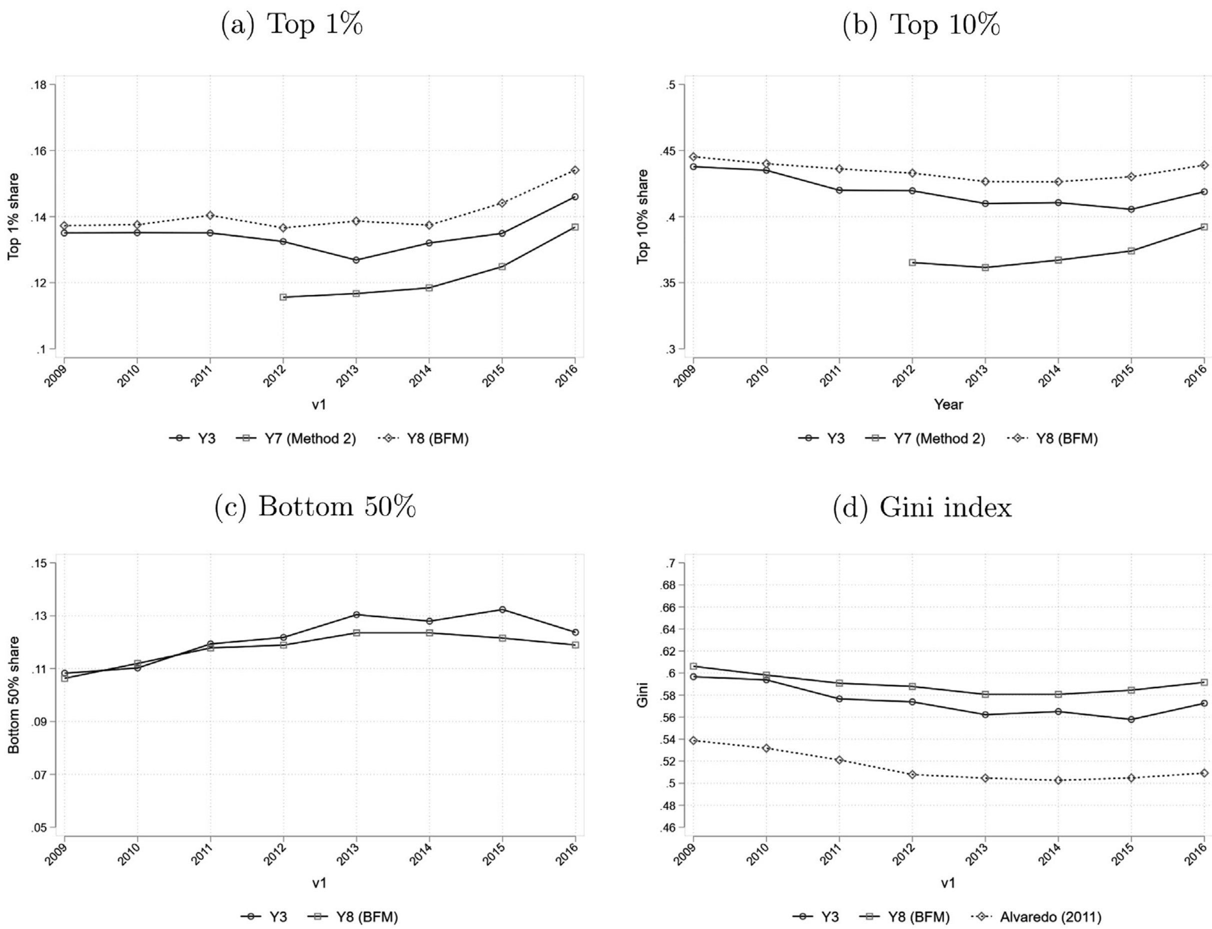


Fig. A3. Pre-tax top income shares, 2009–2016. Method 2 and BFM. *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE). BFM and Alvaredo are the Blanchet et al. (2018) and Alvaredo (2011) survey and tax corrections respectively.

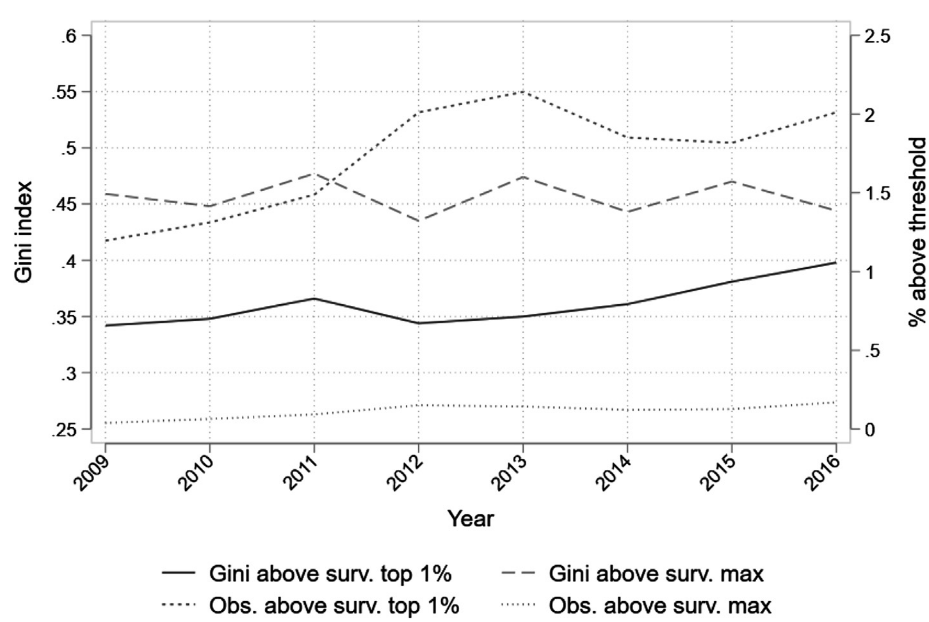
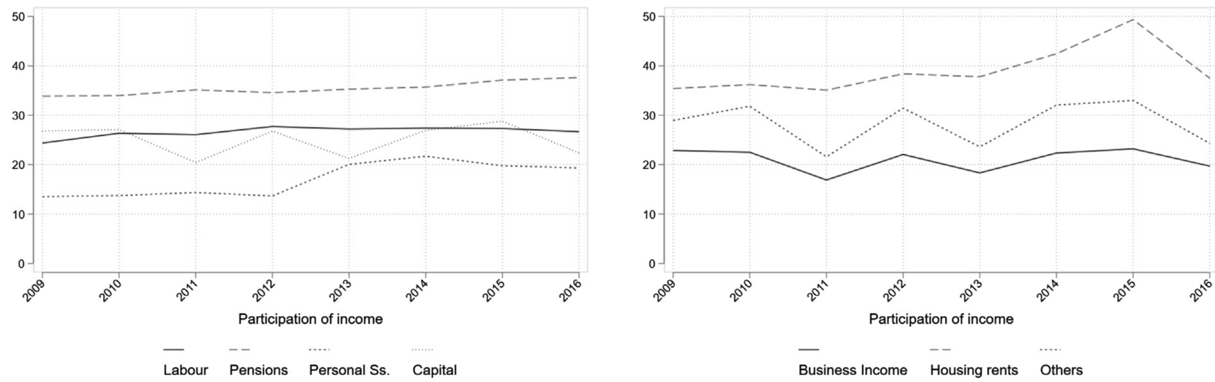
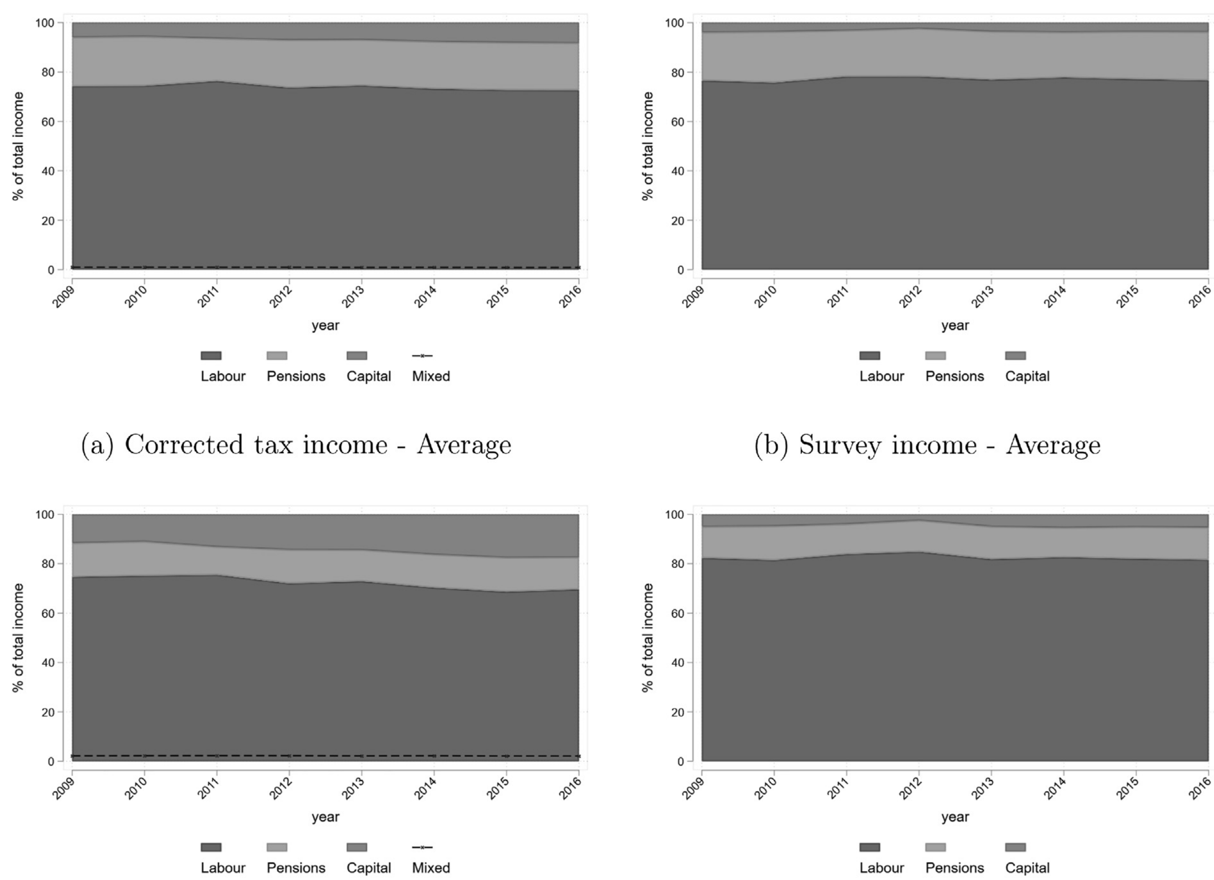


Fig. A4. Inequality trends for selected pre-tax top income groups (above survey's top 1% threshold), 2009–2016. *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE) (estimates in Table A.6). Survey's highest value set at the average of the 50 higher (comparable) income, excluding the highest. All incomes at 2016 prices. The brown and blue lines illustrate the proportion of corrected tax income observations belonging to each group 1) observations with income above the 1% threshold in harmonized survey and below survey's maximum and 2) observations with income above survey's maximum. The green line represents the Gini index computed upon corrected tax income for the subset of observations beyond the survey threshold (groups 1 + 2).



(a) Total income (b) Capital income

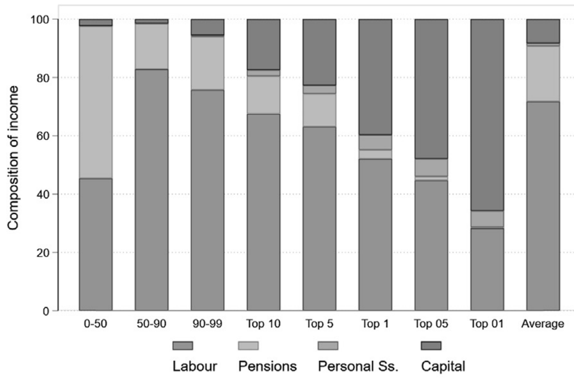
Fig. A5. Participation of women in the top 1% of pre-tax corrected tax income by income source, 2009–2016. *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).



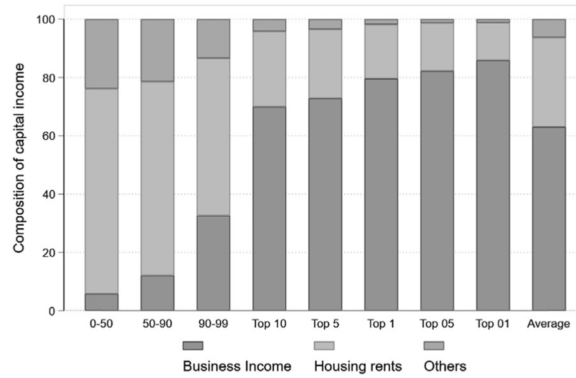
(a) Corrected tax income - Average (b) Survey income - Average

(c) Corrected tax income - Top 10% (d) Survey income - Top 10%

Fig. A6. Composition of income. Pre-tax corrected tax income and survey income, 2009–2016. Average and top 10%. *Note.* Own calculations based on tax records (DGI) and household survey (ECH). In tax records, mixed incomes is depicted as a share of labour income for comparison purposes.



(a) Total income



(b) Capital income

Fig. A7. Income distribution by source and fractile. *Note.* Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

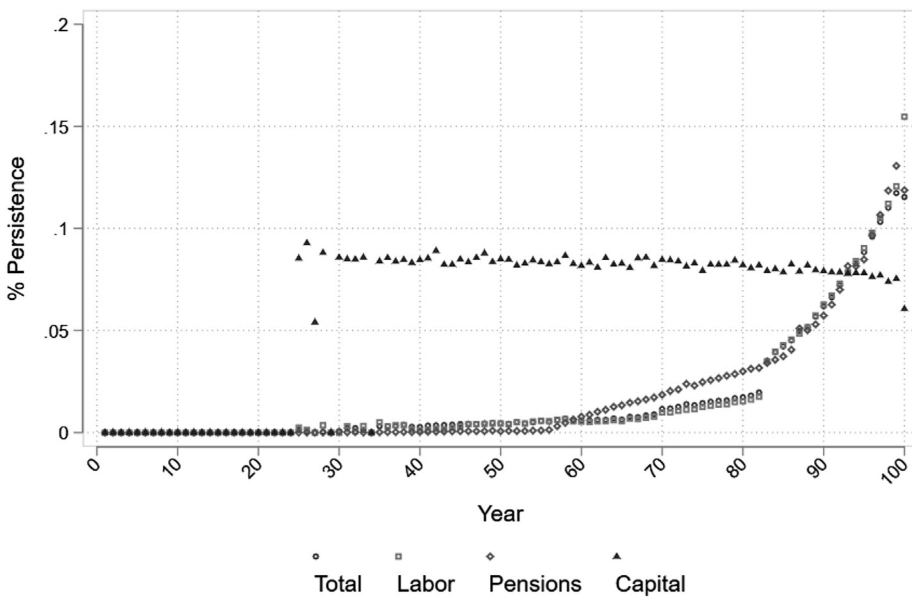


Fig. A8. Effective tax rates by income source. Pre-tax corrected tax income, 2016. *Note.* Own calculations based on tax records (DGI). Effective tax rates for total income and all income sources are depicted.

Table A.1
Characteristics of the data sources used in this study.

Data source	Unit	Population coverage (*)	Income variable used in this article	Time coverage
Tax records	Individuals	Formal earners (potential income tax payers receiving labour, capital or pensions income)	Pre and post tax income by income source. It does not include non taxable income (e.g. cash transfers, imputed owners housing value)	2009–2016
Household survey	Households/ Individuals	All income earners (formal and informal income from all sources).	i) Subset of individuals aged 20 or more with 0 income or being informal earners only; ii) Ratios of informal to formal income for individuals simultaneously receiving both types of income	2009–2016
Linked hh survey - tax records	Households/ Individuals	Sub-sample of the household survey with children aged 0 to 3 in 2012/13 with positive income in tax records and household survey	Ratios of tax records to household survey harmonized income for the subset of linked observations	2012/ 2013
Firms balance sheets	Firms	Firms required to provide annual balance sheets to the tax authorities (annual income above 40000UI)	Withdrawals from firm owners that had not been distributed as profits in next year	2009–2016
Population projections	Individuals	Uruguayan population aged 20 years or more	-	2009–2016

Note. (*) We restrict the population to individuals aged 20 or more.

Table A.2
Top fractiles thresholds by data source, 2009–2016

	2009	2010	2011	2012	2013	2014	2015	2016
Top 1 - threshold	1,036,537	1,157,498	1,302,751	1,526,879	1,656,311	1,912,940	2,100,272	2,404,508
Top 1 - threshold (survey)	980,025	1,048,896	1,112,222	1,121,837	1,316,246	1,499,245	1,650,291	1,792,000
Survey/Tax	95%	91%	85%	73%	79%	78%	79%	75%
Top 10 - threshold	320,095.5	361,134.7	408,598.2	475,083.4	563,590.3	612,658.6	669,908.3	751,771.8
Top 10 - threshold (survey)	334,079.9	361,940.4	411,079.1	458,437.8	520,729.2	579,817.1	644,707.0	701,523.9
Survey/Tax	104%	100%	101%	96%	92%	95%	96%	93%

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE). The first block depicts the top 1%'s share in the tax records and harmonized survey.

Table A.3
Inequality measures- bootstrap confidence intervals (95%). Selected indicators, 2009–2016.

	Gini index			Top 1%			Top 10%			Top 0,1%		
Year	Point est.	Lower b.	Upper b.	Point est.	Lower b.	Upper b.	Point est.	Lower b.	Upper b.	Point est.	Lower b.	Upper b.
2009	0,500	0,497	0,504	13,5%	13,0%	14,1%	43,8%	43,4%	44,2%	50,0%	49,7%	50,4%
2010	0,503	0,499	0,507	13,5%	13,0%	14,3%	43,5%	43,1%	44,0%	50,3%	49,9%	50,7%
2011	0,477	0,472	0,485	13,5%	12,7%	14,8%	42,0%	41,5%	42,8%	47,7%	47,2%	48,5%
2012	0,484	0,480	0,489	13,2%	12,6%	14,1%	42,0%	41,5%	42,6%	48,4%	48,0%	48,9%
2013	0,469	0,464	0,476	12,7%	11,8%	13,7%	41,0%	40,4%	41,7%	46,9%	46,4%	47,6%
2014	0,476	0,473	0,479	13,2%	12,7%	13,6%	41,1%	40,7%	41,4%	47,6%	47,3%	47,9%
2015	0,468	0,463	0,473	13,5%	12,8%	14,4%	40,6%	40,0%	41,2%	46,8%	46,3%	47,3%
2016	0,486	0,482	0,490	14,6%	14,1%	15,4%	41,9%	41,5%	42,4%	48,6%	48,2%	49,0%

Note. Own elaboration based on DGI and ECH. Bootstraps with 100 repetitions.

Table A.4
Redistributive effect of direct taxation. Pre and post-tax corrected tax income, 2009–2016.

	2009	2010	2011	2012	2013	2014	2015	2016
Bottom 50	4.38%	4.71%	4.68%	4.82%	4.79%	5.26%	5.02%	5.22%
50–90	3.81%	3.94%	3.79%	3.69%	3.50%	3.65%	3.30%	3.34%
90–99	−3.58%	−3.64%	−4.05%	−4.16%	−4.14%	−4.61%	−4.58%	−4.49%
Top 10	−5.04%	−5.31%	−5.48%	−5.44%	−5.45%	−5.75%	−5.40%	−5.19%
Top 5	−6.68%	−6.99%	−6.98%	−6.80%	−6.84%	−7.05%	−6.47%	−6.15%
Top 10	−8.31%	−9.03%	−8.50%	−8.20%	−8.36%	−8.14%	−7.03%	−6.50%
Top 0.5	−8.42%	−9.39%	−8.53%	−8.35%	−8.19%	−8.00%	−6.75%	−6.21%
Top 0.1	−7.14%	−8.96%	−7.12%	−6.92%	−5.99%	−5.92%	−4.75%	−4.40%
Gini Index	−0.015	−0.016	−0.017	−0.017	−0.017	−0.018	−0.017	−0.017
Theil Index	−0.074	-0.075	-0.072	-0.098	−0.073	-0.07	-0.052	-0.071

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

Table A.5
Inequality decompositions by income source. 2009–2016. Corrected tax income (Y_3) and harmonized survey income.

		Corrected tax income - Y3							
		2009	2010	2011	2012	2013	2014	2015	2016
Gk	Labour	0.620	0.624	0.585	0.601	0.583	0.590	0.580	0.597
	Pensions	0.819	0.813	0.823	0.810	0.813	0.813	0.812	0.810
	Capital	0.989	0.990	0.991	0.984	0.985	0.986	0.990	0.990
	Mixed	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
Share	Labour	0.774	0.782	0.803	0.767	0.783	0.758	0.750	0.754
	Pensions	0.101	0.098	0.057	0.083	0.069	0.079	0.077	0.075
	Capital	0.106	0.101	0.120	0.130	0.129	0.144	0.155	0.153
	Mixed	0.010	0.010	0.010	0.010	0.009	0.009	0.009	0.009
		Harmonized survey income							
		2009	2010	2011	2012	2013	2014	2015	2016
Gk	Labour	0.650	0.641	0.612	0.597	0.596	0.588	0.594	0.592
	Pensions	0.827	0.820	0.830	0.826	0.825	0.829	0.825	0.819
	Capital	0.967	0.967	0.965	0.961	0.968	0.968	0.967	0.967
Share	Labour	0.852	0.848	0.878	0.893	0.864	0.874	0.868	0.868
	Pensions	0.100	0.107	0.085	0.085	0.088	0.074	0.083	0.081
	Capital	0.047	0.045	0.036	0.022	0.048	0.053	0.049	0.051

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

Table A.6
Gini index above different income thresholds

Year	Top 1% (Corrected survey income)	Top 1% (Corrected tax income)	Max. survey
2009	0.342	0.347	0.459
2010	0.348	0.356	0.448
2011	0.366	0.38	0.477
2012	0.344	0.365	0.435
2013	0.35	0.39	0.474
2014	0.361	0.38	0.443
2015	0.381	0.402	0.47
2016	0.398	0.417	0.444

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

Table A.7
Industries ranking according to their share in top income earners income by income source (ranked by top 1% of corrected tax income - 2016).

	Labour income			
	Top 1	Top 5	Top 10	Average
Human healthcare activities - hospitals	23.3%	11.4%	9.0%	3.7%
Financial intermediation	8.8%	8.0%	4.5%	0.7%
General public administration	4.7%	10.9%	12.1%	8.6%
Other human health act.	2.3%	2.5%	2.6%	2.1%
Medical and dental healthcare	1.8%	1.4%	1.3%	1.0%
Non-life insurance	1.5%	1.9%	1.4%	0.4%
Other professional and scientific act.	1.5%	3.1%	3.1%	1.3%
Activities of collection agencies	1.4%	0.6%	0.4%	0.3%
Wholesale of pharmaceutical and medical goods	1.3%	1.0%	0.7%	0.3%
Manufacture of pharmaceuticals and medicinal products	1.2%	1.1%	1.0%	0.4%
	Liberal Professions			
	Top 1	Top 5	Top 10	Average
Human healthcare activities - hospitals	7.9%	5.6%	4.9%	3.7%
Non-life insurance	4.4%	3.7%	3.3%	2.9%
Construction of buildings	2.9%	2.8%	2.7%	2.8%
Medical and dental healthcare	2.9%	1.8%	1.7%	1.2%
General public administration	2.4%	2.9%	2.8%	2.2%
Other professional and scientific act.	1.8%	1.3%	1.2%	1.1%
Processing and preserving of meat	1.5%	1.7%	1.6%	1.4%
Manufacture of pharmaceuticals and medicinal products	1.4%	1.4%	1.3%	1.0%
Real estate act.	1.0%	0.8%	0.7%	0.6%
Pre-primary and primary education	1.0%	1.0%	1.0%	0.9%
	Business income			
	Top 1	Top 5	Top 10	Average
Human healthcare activities - hospitals	4.3%	3.9%	3.5%	1.8%
Activities of collection agencies	2.4%	2.5%	2.5%	1.3%
Raising of cattle	2.0%	1.8%	1.8%	1.0%
Medical and dental healthcare	1.7%	2.0%	1.9%	1.1%
Retail sale of automobile fuel	1.6%	1.4%	1.3%	0.8%
Other professional and scientific act.	1.5%	1.5%	1.3%	0.7%
Construction of buildings	1.4%	1.3%	1.2%	0.7%
Freight transport by road	1.4%	1.0%	1.0%	0.6%
Retail sale in non-specialized stores	1.4%	1.5%	1.3%	0.8%
Gambling and betting activities	1.1%	1.3%	1.3%	0.9%

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

Table A.8
Probability of belonging to the top 1% (by gender, versus bottom 99% or centiles 90–99, 2016. Probit estimates. Marginal effects).

	Top 1 vs bottom 99%			Top 1 vs remaining Top 10%		
	Total	Female	Male	Total	Female	Male
Male	0.001***			0.0153***		
	(0.000)			(0.00130)		
Age	0.000***	3.80e-05***	0.000966***	0.000488***	0.000298***	0.00529***
	(0.000)	(1.48e-06)	(4.67e-05)	(1.70e-05)	(1.65e-05)	(0.000360)
Age2	−0.000***	−1.54e-08***	−4.28e-06***	−1.89e-07***	−1.01e-07***	−2.13e-05***
	(0.000)	(7.50e-10)	(4.50e-07)	(9.39e-09)	(8.65e-09)	(3.50e-06)
Liberal professional	0.103***	0.0208***	0.0350***	0.332***	0.142***	0.189***
	(0.004)	(0.000744)	(0.000767)	(0.00994)	(0.00605)	(0.00497)
Capital Inc. recipient	0.022***	0.0166***	0.0237***	0.0555***	0.0971***	−0.0244***
	(0.000)	(0.000254)	(0.000386)	(0.00140)	(0.00214)	(0.00426)
Dividends	0.030***	0.0174***	0.0396***	0.173***	0.106***	0.203***
	(0.000)	(0.000496)	(0.000632)	(0.00289)	(0.00419)	(0.00401)
Property rents	0.011***	0.00530***	0.0142***	0.0684***	0.0353***	0.0776***
	(0.000)	(0.000250)	(0.000360)	(0.00160)	(0.00203)	(0.00236)
Others	0.006***	0.00135***	0.00856***	0.0557***	0.0189***	0.0697***
	(0.000)	(0.000510)	(0.000571)	(0.00301)	(0.00457)	(0.00407)
Labour Inc. recipient	0.002***	0.000342	0.00691***	−0.0133**	−0.0177**	0.00212
	(0.000)	(0.000610)	(0.000863)	(0.00554)	(0.00754)	(0.00684)
Pensioners	−0.000	−0.00292***	−0.00477***	0.00662***	−0.0195***	−0.0179***
	(0.000)	(0.000248)	(0.000389)	(0.00179)	(0.00221)	(0.00282)
Multi-job - Dependent	0.018***	0.0114***	0.0213***	0.0803***	0.0670***	0.105***
	(0.001)	(0.000230)	(0.000284)	(0.00208)	(0.00228)	(0.00193)
Self-employed	0.004***	0.00502***	0.0103***	0.0422***	0.0483***	0.0789***
	(0.000)	(0.000594)	(0.000718)	(0.00385)	(0.00573)	(0.00522)
Dependent/Self-employed	0.031***	0.0158***	0.0268***	0.140***	0.103***	0.146***
	(0.001)	(0.000336)	(0.000449)	(0.00428)	(0.00305)	(0.00303)
Manufacturing	0.005***	0.00347***	0.00571***	0.0133***	0.0293***	−0.00849*
	(0.000)	(0.000576)	(0.000638)	(0.00381)	(0.00641)	(0.00508)
Electricity, gas, air	0.003***	0.000750	0.00531***	−0.00424	−0.00727	0.000557
	(0.001)	(0.00117)	(0.00102)	(0.00535)	(0.00998)	(0.00686)
Construction	−0.002***	−0.000281	−0.00261***	−0.0245***	−0.00192	−0.0265***
	(0.001)	(0.000858)	(0.000773)	(0.00464)	(0.00912)	(0.00586)
Wholesale and retail trade	0.004***	0.00232***	0.00606***	0.0172***	0.0310***	0.0156***
	(0.000)	(0.000554)	(0.000642)	(0.00380)	(0.00625)	(0.00494)
Transportation, Information and communication	0.000	−0.00235***	0.00187***	−0.0183***	−0.0285***	−0.0131***
	(0.000)	(0.000624)	(0.000655)	(0.00387)	(0.00647)	(0.00499)
Accommodation and food service	−0.002**	−0.00605***	0.00182	0.00225	−0.0381***	0.0149
	(0.001)	(0.000994)	(0.00122)	(0.00717)	(0.0106)	(0.00960)
Real estate activities	−0.002***	−0.00284***	−0.00295***	−0.0163**	−0.0193*	−0.0183**
	(0.001)	(0.000957)	(0.00111)	(0.00661)	(0.0104)	(0.00865)
Professional and technical activities	0.002***	−0.00112*	0.00620***	0.00381	−0.0150**	0.0173***
	(0.000)	(0.000611)	(0.000767)	(0.00426)	(0.00646)	(0.00575)
Administrative and support service	−0.001	−0.000142	−0.00197**	−0.00267	0.0137*	−0.000449
	(0.001)	(0.000643)	(0.000922)	(0.00540)	(0.00812)	(0.00719)
Public administration and defence	0.003***	0.00193***	0.00394***	0.0166***	0.0116*	0.00932
	(0.001)	(0.000623)	(0.000799)	(0.00427)	(0.00641)	(0.00580)
Education	−0.006***	−0.00712***	−0.00492***	−0.0511***	−0.0577***	−0.0432***
	(0.001)	(0.000653)	(0.000903)	(0.00457)	(0.00663)	(0.00649)
Social work activities	−0.010***	−0.00852***	−0.0121***	−0.0742***	−0.0644***	−0.0776***
	(0.001)	(0.00122)	(0.00212)	(0.00936)	(0.0112)	(0.0146)
Arts, entertainment	−0.006***	−0.00845***	−0.00405***	−0.0291***	−0.0525***	−0.0122
	(0.001)	(0.00107)	(0.00127)	(0.00712)	(0.0104)	(0.00960)
Other service activities	−0.004***	−0.00767***	−0.00177	−0.0319***	−0.0659***	−0.0199**
	(0.001)	(0.00104)	(0.00120)	(0.00638)	(0.00993)	(0.00845)
Hospital activities	0.071***	0.0151***	0.0343***	0.274***	0.115***	0.193***
	(0.007)	(0.00112)	(0.00206)	(0.0201)	(0.00972)	(0.0139)
Medical and dentral activities	0.026***	0.00862***	0.0195***	0.119***	0.0616***	0.102***
	(0.004)	(0.00127)	(0.00227)	(0.0175)	(0.0110)	(0.0154)
Other health activities	0.024***	0.00881***	0.0171***	0.125***	0.0704***	0.0924***
	(0.003)	(0.00118)	(0.00217)	(0.0168)	(0.0103)	(0.0148)
Financial service activities	0.023***	0.00376***	0.0201***	0.0913***	0.0169***	0.0911***
	(0.001)	(0.000584)	(0.000738)	(0.00640)	(0.00613)	(0.00532)
Insurance	0.007***	−0.000810	0.0121***	0.0522***	0.00829	0.0577***
	(0.001)	(0.000834)	(0.00115)	(0.00797)	(0.00805)	(0.00780)
Auxiliary activities to finanical ss.	0.012***	0.00366***	0.0128***	0.0474***	0.0169**	0.0564***
	(0.001)	(0.000823)	(0.00114)	(0.00794)	(0.00824)	(0.00818)
Stock corporation	0.007***	0.00698***	0.00986***	0.0175***	0.0118	0.0271***
	(0.000)	(0.000754)	(0.000989)	(0.00599)	(0.00929)	(0.00840)
Public sector	0.006***	0.00606***	0.00775***	0.00389	−0.00487	0.0132
	(0.000)	(0.000791)	(0.00110)	(0.00625)	(0.00949)	(0.00901)
Observations	1,952,876	986,420	966,377	240,044	102,470	137,561

Note. Own calculations based on population projections (CELADE-INE, 2016), tax records (DGI) and household surveys (INE).

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2021.105783.

References

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

Abowd, J. M., & Stinson, M. H. (2013). Estimating measurement error in annual job earnings: A comparison of survey and administrative data. *Review of Economics and Statistics, 95*(5), 1451–1467.

Adriaans, J., Valet, P., & Liebig, S. (2020). Comparing administrative and survey data: Is information on education from administrative records of the german institute for employment research consistent with survey self-reports? *Quality & Quantity, 54*(1), 3–25.

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., & Saez, E. (2013). The top 1 percent in international and historical perspective. *Journal of Economic Perspectives, 27*(3), 3–20.

Alvaredo, F., & Gasparini, L. (2015). Recent trends in inequality and poverty in developing countries. In A. Atkinson & F. Bourguignon (Eds.). *Handbook of Income Distribution* (volume 2, pp. 697–805). Elsevier.

Alvaredo, F., & 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., Arim, R., & Yapor, M. (2016). Decomposing inequality changes in uruguay: the role of formalization in the labor market. *IZA Journal of Labor & Development, 5*(1), 1–20.

Amarante, V., & 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., & 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., & Voitchovsky, S. (2018). Top incomes and the gender divide. *The Journal of Economic Inequality, 16*(2), 225–256.

Atkinson, A. B., Piketty, T., & Saez, E. (2011). Top incomes in the long run of history. *Journal of Economic Literature, 49*(1), 3–71.

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.

Bertrand, M., & Mullainathan, S. (2001). Are ceos rewarded for luck? the ones without principals are. *The Quarterly Journal of Economics, 116*(3), 901–932.

Bittencourt, G., Carracelas, G., Doneschi, A., and Reig Lorenzi, N. (2009). Tendencias recientes de la inversión extranjera directa en uruguay. Documento de Trabajo/FCS-DE; 27/09.

Bivens, J., & Mishel, L. (2013). The pay of corporate executives and financial professionals as evidence of rents in top 1 percent incomes. *Journal of Economic Perspectives, 27*(3), 57–78.

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

Boschini, A., Gunnarsson, K., & Roine, J. (2020). Women in top incomes–evidence from sweden 1971–2017. *Journal of Public Economics, 181* 104115.

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., & Amábile, F. (2013). *Social spending, taxes and income redistribution in Uruguay*. The World Bank.

Burdín, G., De Rosa, M., Vigorito, A., and Vilá, J. (2020). Was Falling Inequality in All Latin American Countries a Data-Driven Illusion? Income Distribution and Mobility Patterns in Uruguay 2009–2016. IZA Discussion Papers 13070, Bonn.

Burdín, G., Esponda, F., & Vigorito, A. (2014). 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., & 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.

Burkhauser, R. V., Hérault, N., Jenkins, S., & Wilkins, R. (2018). Survey under-coverage of top incomes and estimation of inequality: What is the role of the UK's SPI adjustment? *Fiscal Studies, 39*, 213–240.

CEPAL (2020). Brechas de género en los ingresos laborales en el uruguay.

Charpentier, A. and Flachaire, E. (2019). Pareto models for top incomes.

Chudnovsky, D., & López, A. (2007). Inversión extranjera directa y desarrollo: la experiencia del mercosur. *Revista de la CEPAL*.

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

Cowell, F.A. (2011). Measuring Inequality. Oxford University Press, Oxford, third edition.

Cowell, F. A., & Flachaire, E. (2015). Statistical methods for distributional analysis. *Handbook of Income Distribution* (volume 2, pp. 359–465). Elsevier.

De Rosa, M., Flores, I., & Morgan, M. (2020). *Inequality in Latin America Revisited: Insights from Distributional National Accounts*. WIL Technical Notes.

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

Domínguez-Amorós, M., Batthyány, K., & Scavino, S. (2021). Gender gaps in care work: Evidences from argentina, chile, spain and uruguay. *Social Indicators Research*, 1–30.

ECLAC. (2019). *Social Panorama of Latin America 2019*. ECLAC.

Espino, A., Isabella, F., Leites, M., & Machado, A. (2017). Do women have different labor supply behaviors? evidence based on educational groups in uruguay. *Feminist Economics, 23*(4), 143–169.

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

Feenberg, D. R., & 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.

De Rosa, M. and Vilá, J. (2020). Distributing the missing third: growth and falling inequality in uruguay 2009-2016. Serie Documentos de Trabajo; 05/20.

Flachaire, E., Lustig, N., and Vigorito, A. (2021). Underreporting of top incomes and inequality: An assessment of correction methods using linked survey and tax data. Technical report, Paper presented to the 2021 Conference of the International Association for Research in Income and Wealth.

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

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

Hansen, N.-J. H., Harmenberg, K., Öberg, E., & Sievertsen, H. H. (2021). Gender disparities in top earnings: measurement and facts for denmark 1980–2013. *The Journal of Economic Inequality*, 1–16.

Higgins, S., Lustig, N., Vigorito, A., et al. (2018). The rich underreport their income: Assessing bias in inequality estimates and correction methods using linked survey and tax data. *Ecineq WP, 475*.

Instituto Nacional de Estadística (2013). Encuesta de nutrición, desarrollo infantil y salud, endis.

Instituto Nacional de Estadística (2021). Encuestas continuas de hogares.

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

Jenkins, S. P. (2017). Pareto models, top incomes and recent trends in UK income inequality. *Economica, 84*, 261–289.

Kopczuk, W., & Zwick, E. (2020). Business incomes at the top. *Journal of Economic Perspectives, 34*(4), 27–51.

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

Lemieux, T., & Riddell, W. C. (2015). *Who are canada's top 1 percent? Income Inequality*. The Canadian Story.

Lerman, R. I., & Yitzhaki, S. (1985). Income inequality effects by income source: A new approach and applications to the united states. *The Review of Economics and Statistics*, 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., & Ortiz-Juarez, E. (2011). The decline in inequality in latin america: How much, since when and why. *Since When and Why, 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.

Peluffo, A. (2015). Foreign direct investment, productivity, demand for skilled labour and wage inequality: An analysis of uruguay. *The World Economy, 38*(6), 962–983.

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.

SEDLAC (CEDLAS and The World Bank).

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

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

Smith, M., Yagan, D., Zidar, O., & Zwick, E. (2019). Capitalists in the twenty-first century. *The Quarterly Journal of Economics, 134*(4), 1675–1745.

Souza, P. H., & 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, Leopoldo, Ciaschi, Matías, & Galeano, Luciana (2018). Income distribution in latin america: The evolution in the last 20 years: A global approach. *Universidad Nacional de La Plata, Centro de Estudios Distributivos, Laborales y Sociales (CEDLAS), La Plata* 234.

Zucman, G. (2013). The missing wealth of nations: Are europe and the us net debtors or net creditors? *The Quarterly Journal of Economics, 128*(3), 1321–1364.

Zucman, G. (2014). Taxing across borders: Tracking personal wealth and corporate profits. *Journal of Economic Perspectives, 28*(4), 121–148.