The Joint Distribution of Income and Wealth in Uruguay

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This paper analyzes the joint distribution of income and wealth in Uruguay, and compares it to that of Chile, Spain and the U.S. using data from Surveys of Household Finances and Wealth. First, we analyze income and wealth separately and find that wealth is much more concentrated and notably more asymmetric than income. Afterwards, we provide non-parametric estimation of copulas for income and wealth. As expected, high income households are among the wealthiest, while low income households are mostly in the bottom of the wealth distribution, but dependence at the top is much stronger. Although this fact is observed in all the economies analyzed, by performing a test of equality between copulas we find that the pattern of dependence significantly varies across countries, except for the couple of Spain-Uruguay. Finally, we assess for the sources of income and wealth heterogeneity in Uruguay and conclude that education strongly influences income, wealth and the relationship between them. However, most of the wealth heterogeneity and some remarkable features of its relationship with income (in particular the peak at the top of the joint distribution) are not explained by the household characteristics commonly used to study income.

JEL Classification: C4, C31, D31

Keywords: income, wealth, inequality, copula, non-parametric estimation

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Resumen

Este artículo analiza la distribución conjunta del ingreso y la riqueza en Uruguay, y la compara con la correspondiente a Chile, España y Estados Unidos usando datos de encuestas sobre las finanzas y la riqueza de los hogares. En primer lugar, analizamos separadamente el ingreso y la riqueza, encontrando que la riqueza está mucho más concentrada y es notablemente más asimétrica que el ingreso. En segundo lugar, realizamos estimaciones no paramétricas de las copulas ingreso-riqueza. Como es esperable, los hogares de altos ingresos son también los más ricos, mientras que los hogares de bajos ingresos se ubican principalmente en la parte inferior de la distribución de la riqueza, siendo la dependencia en la parte superior mucho más marcada. Aunque este hecho es observado en todos los países analizados, realizando un test de igualdad de copulas encontramos que la hipótesis de igualdad de copulas es rechazada en todos los casos, excepto para el par España-Uruguay. Finalmente, estudiamos las fuentes de heterogeneidad del ingreso y la riqueza en Uruguay y concluimos que la educación tiene una marcada influencia en el ingreso, la riqueza y en la relación entre ambas. Sin embargo, la mayor parte de la heterogeneidad de la riqueza, y algunas características importantes de la relación de esta variable con el ingreso (en particular la fuerte asociación de estas variables en la parte superior de la distribución conjunta) no son explicadas por las características de los hogares que se utilizan habitualmente para estudiar la distribución del ingreso.

Clasificación JEL: C4, C31, D31
Palabras clave: ingreso, riqueza, desigualdad, copula, estimación no paramétrica

1 Introduction

Considerable literature on economic inequality analyzes the income distribution across households in an effort towards measuring well-being and inequality. Nevertheless, economic inequality has a multidimensional nature and other variables such as earnings, opportunities, consumption or wealth may also be analyzed. Aiming to account for these dimensions, a new strand of the literature is concerned with the distribution of wealth across households and its relationship with income.

Income and wealth links are important for taxation and distribution policy, or to study wealth accumulation and development. Moreover, income and wealth are both relevant for consumption, labor supply and investment household decisions. However, due to lack of available information we know little about the empirical distribution of wealth and its relationship with income. Recent availability of data from Financial Surveys has allowed the study of income and wealth distributions, deriving important results for developed countries (see e.g. Jäntti, et al., 2015). However, the analysis still raises questions regarding how to address the dependence between income and wealth, or how to link the recent analysis on wealth distribution with the vast knowledge on income inequality.

Meanwhile, this new strand of literature has been more concerned with developed countries and it has not been widely extended to emerging economies. More precisely, it has not been extended to Latin America, a region considered by the literature on income inequality as one of the most unequal. Analysing income and wealth distributions and their degree of dependence in emerging economies such as Latin America, may be a matter of interest to assess for different factors such as access to financial services or strength of local institutions which are usually different in developed and developing economies.

In this paper we analyze income and wealth distribution in Uruguay, while we compare it to those of Chile, Spain and the US. Chile and Uruguay are the only Latin American countries with similar surveys collecting data on households' wealth and finances. Also, both economies are usually ranked at the top of Latin America in many indicators such as GDP per capita or Human Development Index (HDI), while ranked at the bottom of others such as poverty rates (CEPAL). However, previous studies show that they differ greatly on income distribution. Uruguay is the country in which income is more equally distributed in Latin America, while Chile ranks in the middle (CEPAL). Meanwhile, Spain and the US are two countries which may account for different factors at the time of a cross-country comparison.The former is a European country to which Chile and Uruguay are historically tied. The latter is the largest economy and an Anglo-Saxon country with different habits and preferences regarding wealth management when compared to the Ibero-American countries under analysis (Badarinza, et al., 2016).

We use household-level data collected in specialized Financial Surveys closely related to each other. For Uruguay, we use data from the first wave of the Encuesta Financiera de los Hogares Uruguayos (EFHU), for Chile we use data collected in the Encuesta Financiera de los Hogares (EFH). Both surveys are closely related to the Spanish Encuesta Financiera de las Familias (EFF) and the US Survey of Consumer Finances (SCF) allowing us to provide cross-country comparisons of income and wealth distribution across households.

Firstly, we make an univariate analysis of income and wealth. We analyze assets and liabilities while describing the most relevant differences between the economies considered. As a major finding, non financial assets and especially the main residence, accounts for a larger fraction of total assets in Chile and Uruguay than in the US, while Spain remains in the middle. Debt for acquiring the main residence accounts for the largest fraction of total debt for all the countries under analysis, but is more frequent in the US and Spain than in the other countries under analysis.

Afterwards, we analyze the univariate distribution of income and wealth and provide commonly used indicators to assess for inequality, such as the Gini coefficient and the "mean/median" ratio. Also, we estimate non-parametric kernel densities for each variable. Along with previous findings, wealth is much more concentrated than income in all the analyzed countries. Besides, income is more concentrated in Chile than in the other economies, while Spain appears as the country in which income is more equally distributed. On the other hand, wealth distribution is much more concentrated in the US than in the other countries. Also, it appears to be similarly distributed in Chile and Uruguay, despite the fact that income is much more concentrated in the former.

The literature on this topic unveils different country rankings for income and wealth which motivates the analysis on the joint distribution of both variables. Hence, we construct empirical smoothed kernel copulas to assess for the dependence between both variables along the entire joint distribution (Chen and Huang, 2007; Kennickell, 2009; Jäntti et al. 2015). Along with previous findings, in all the countries analyzed, top income households are among the wealthiest, while low income households are likely to be more frequent among the poorest. However, such dependence is stronger at the top of the joint distribution. In a cross country comparison, we notice that the kernel estimated copulas for Chile, Spain and Uruguay are similar, while that of the US looks very different, in particular because of the sharp peak at the top income and top wealth corner. Although at a quick glance, the copulas look very similar, they may hide differences in the true dependence between the variables. Thus, for further analysis, we perform tests for equality between copulas for each pair of countries using the Rémillard and Scaillet (2009) non-parametric test. The hypothesis of equality between copulas is only supported by the data for the pair Spain-Uruguay.

Aiming to account for sources of heterogeneity of income and wealth, we also provide mean regression estimates for income and wealth in Uruguay (see e.g. Arrondel, et al., 2014). We conclude that years of schooling is the main source of heterogeneity of income, and also influences wealth, but inheritances have the highest explanatory power for wealth. Life-cycle, the family structure and the region of residences also play a role. Finally, we find that education is a relevant driving force for the relationship between income and wealth. However, most of the wealth variation and its dependence with income remains unexplained.

We contribute to the literature in various ways. Firstly, we provide estimations of non-parametric smoothed kernel copulas for income and wealth. Secondly, we formally assess for differences in the dependence of income and wealth between the different countries by performing a non-parametric test for equality between copulas. Finally, we identify the influence of several household characteristics on the dependence between income and wealth in Uruguay.

The paper is organized as follows. The next section describes the data. Section three presents the household balance sheet items through the analysis of the participation rate and allocation of assets and liabilities. The fourth section analyzes the univariate distributions of income and wealth. The fifth section presents the methods we use to study the joint distribution of income and wealth. Section six presents and analyzes the main results from across country estimates as well as those about the sources of household heterogeneity for income and wealth and their pattern of dependence in Uruguay. The final section concludes.

2 Data

We use data from Surveys of Household Finances and Wealth for each country. For Spain we use data collected in the 2011 wave of the Encuesta Financiera de las Familias (EFF)[1], while for the US we use the 2013 wave of the Survey of Consumer Finances (SCF). For Chile, data comes from the 2014 wave of the Encuesta Financiera de los Hogares (EFH) and for Uruguay we use data collected in the first wave of Encuesta Financiera de los Hogares Uruguayos (EFHU) during 2013 and 2014 (see table 1).

The SCF is conducted from the nineties on a triennial basis as a cross-sectional survey, by the University of Chicago.[2] The EFF is conducted by Banco de España also for every three year period since 2002, and each subsequent wave has both a panel structure and a refresh sample. The Chilean EFH of the Banco de Chile is also a panel dataset and its first wave was collected in 2007, while the Uruguayan EFHU (conducted by dECON-UDELAR and sponsored by the Banco Central del Uruguay and Ministerio de Economía) corresponds to 2013-2014 and has only one wave. Both the EFH and the EFHU are similar to the SCF and the EFF. They were designed using the same technical features, especially of the EFF, including: the questionnaire, the sample design, the type of interview and the selection of the family member to be interviewed, and the methods used to deal with item non-response.

Consequently, there are important similarities among these surveys that allow us to use them to perform cross-country comparisons. Firstly, used surveys collect similar information on household assets, liabilities, income, expenditure and socio-economic data on household members. Secondly, their design oversamples high income households. This serves to account for the fact that there are assets held by a small fraction of the population (Kennickell, 2005, 2007). Another similarity between the analyzed surveys is that they all use stochastic multiple imputation to deal with the well known item non-response

[1]Microdata of the 2014 wave of the EFF is not available yet.

[2]The SCF is sponsored by the United States Federal Reserve Board in cooperation with the U.S. Treasury Department.

bias, an important characteristic in household financial surveys.

It is important to note that, despite the similarities mentioned above that, performing accurate cross-country comparisons is not straightforward since each survey has its own specificities. Firstly, income data for Chile and Uruguay is collected after tax, while in the US and Spain income data is before tax. For the case of the US, data on taxes paid by households were computed using TAXSIM program. [3] However, this was not possible for Spain, therefore income for that country is considered before taxes, which poses a considerable restriction, since the impact of taxes on inequality has been well documented by the literature (OECD, 2012). Secondly, the Chilean survey EFH does not collect information on household business, which constitutes a limitation since firm ownership has been recognized as a major determinant of the long right tail of the wealth distribution (Cagetti, De Nardi, 2008). Therefore, to compare data from Uruguay and Chile, we provide some indicators on Uruguayan wealth with and without business. From our point of view, these issues strengthen the attractiveness of modelling copulas to perform cross-country comparisons, since it is expected that they have a stronger influence on the income and wealth distributions than over the rankings within them.

3 Households' balance sheets

This section briefly explains how we compute net wealth and provides data on the composition of household balance sheets. Badarinza et al. (2016) compare household participation rates, asset and debt allocations for 13 developed economies including some European countries, the US, Canada and Australia. They assess for differences across countries, and relate them to cultural habits, institutional framework and economic features. Such analysis is beyond the scope of this paper. However, we point out some remarkable cross-country similarities/differences among the 4 countries under analysis and make use of previous findings on this topic to contextualize our results.

As usual in the literature, in this paper assets are composed by financial and non financial assets. Financial assets account for deposits, transactions accounts, bonds, stocks, retirement funds and mutual funds. Non-financial assets are composed by the main residence, other real estate, business ownership, vehicles and other valuables such as jewerly or art objects. Liabilities include all the outstanding debt owned by households. We consider debts for purchasing the main residence and other real estate (mortgage and non-mortgage credit) and other debts for purchasing durable and non durable goods, education loans and credit card outstanding balances.

Table 2 reports participation rates for assets and liabilities computed as the percentage of households owning each asset/debt. The participation rate for the main residence is quite similar in Uruguay, Chile and the US. Furthermore, they are also similar to those

[3] TAXSIM is a NBER program which computes federal, state and payroll taxes for households in different surveys. For the case of the SCF, we compute federal and payroll taxes since geographical information is not disclosed. More information on TAXSIM program may be found in http://users.nber.org/ taxsim/

registered in other countries such as Italy, the UK, Australia, Canada and Finland, where the proportion of households that owns the main residence is between 60 and 70 percent. Meanwhile, the participation rate for the main residence in Spain is well above that: around 83%. In Slovenia and Slovakia ownership rates are also above 80%. On the other side, Germany is the country with the lowest ownership rate (44%), while this figure is around 55% in France and the Netherlands.[4]

Housing ownership decisions have been extensively studied. The literature points out the existence of incentives and disincentives at the time of buying the main residence. On the one hand, in some countries tax systems may enhance home ownership by specific tax credits. In addition, the presence of moral hazard and incomplete markets can make rent prices greater than the cost of using the property. Moreover, real estate is commonly used as an investment or as collateral for loans. On the other side, disincentives can be related to transaction cost and the opportunity cost of including a risky, non-liquid and non-divisible asset in household portfolio (Sanroman, 2006).

In Uruguay, inflation was considerable high during the second half of the 20th century and home ownership as well as other real estate was traditionally viewed as a safe investment with respect to others. In recent years, inflation has fallen to one digit figures but investing in local currency assets is still considered risky. In addition, a personal income tax system was introduced in 2007, which includes some benefits for home buyers.

According Badarinza et al. (2016), the main residence property is the single most valuable asset held by households except in Germany (where it accounts for 29.9% of total assets against 30% of that for bank deposits). In addition, it represents half or even more of total household assets value in several countries such as Greece, Italy, Slovakia, Slovenia and Spain. On average, real assets represent 85% of total gross assets in Europe (Cowell and Van Kerm, 2015). Our data shows a similar picture for Chile and Uruguay where home ownership accounts for 63 and 55 percent of total assets, respectively (see table 3). Besides, by adding other real estate we observe that around 80% of household assets in Chile and Uruguay are real estate investments. The study of the evolution of real estate prices and their impact on financial system stability is a very active field of research, especially since the last financial crisis (see e.g.: Cerutti et al., 2017; Agnello and Schuknecht, 2011). For the case of Uruguay, Ponce (2014) calibrates a model for the fundamentals of housing prices and finds that fundamentals have systematically increased since the 2002 Uruguayan crisis, while real housing prices has been fluctuating around them. He also shows that real prices fluctuate more than what is justified by fundamentals.

Another interesting strand of the literature focuses on the effect of home ownership on labor mobility: Head and Lloyd-Ellis (2012) conclude that in the US homeowners accept job offers from other cities at a lower rate than renters do, generating a link between

[4] We take results of Badarinza et al. (2016) and the Household Finances Survey and Consumption Network (HFCN) to complement our data. The Household Finances Survey and Consumption Network (HFCN) conducts the Eurosystem's Households Finance and Consumption Survey (HFCS), includes financial household-level data from countries belonging to the Euro Area. The first wave was collected during 2009-2010.

homeownership and unemployment both at the city level and in the aggregate. However, this topic has not been yet studied in Uruguay.

Concerning business, the participation rate is substantially larger in Uruguay than in Spain and the US. However, a broad definition for business is used, since self-employees and owners of small business are included. To the extent that the informal economy is larger in Uruguay than in the developed economies, self employment may account for a larger portion of workforce than in the developed economies. Unfortunately, the Chilean survey does not collect information about this item. For EU-countries, according to the HFCN, an average 11% of households own a business; but in countries like Italy or Spain these figures were 15% (2010) and 18.4% respectively, closer to that of Uruguay.

The participation rate for financial assets is substantially lower in Uruguay (49%) than in Chile (82%), where it is also well below figures observed for developed countries. Badarinza et al. (2016) report that the average participation rate is above 90% in all the countries analyzed, except for Greece. Notice however, that the composition of household portfolio substantially differs among developed countries: equity and risky asset shares range from 5% in Greece and 11% in Italy to 50% in the US. Numerous studies have been devoted to study this phenomenon and various puzzles are present in this literature, among them: the well-known "home bias puzzle" that asks why households typically do not diversify internationally their financial portfolios, being that they have the opportunity to do so (Cooper et al., 2013; Bekaert et al., 2015).

Financial markets in emerging economies, such as Chile and Uruguay, are in an early stage of development. In particular, there are almost no markets for equities in Uruguay, and the bank system is characterized by an oligopoly structure where the active interest rates are very high and the passive ones very low, especially for family loans. However, investing in international financial markets is allowed and relatively easy in Uruguay. Thus, the home bias puzzle is still present. Low levels of financial literacy may play a key role in explaining why the majority of Uruguayan households do not invest in financial assets at all, and only 2 percent of households include risky assets in their financial portfolio.

There are some additional remarkable differences between Spain and the US in terms of financial investments. In the latter a larger fraction of financial assets belongs to the pension system, while this figure is low for the other countries analyzed. Also evidence for Anglo-Saxon countries, as the US, indicates that financial assets and retirement funds account for a larger share of total assets than in the Southern European countries, where non financial assets and especially the main residence represent a larger fraction of total assets (Badarinza et al., 2016). Taking that into account, figures for Chile and Uruguay seems to be closer to those of Spain. Some similarities/dissimilarities among countries' Social Security systems would be behind such facts.

Turning to liabilities, almost 50% of Uruguayan households are indebted; a similar figure to that of Spain. In Chile and the US this figure is near 75%. The proportion of indebted households in Uruguay is close to the average of the Euro Area, which was 43% in 2009-2010 (HFCN). An important characteristic observed in data is that the participation rate for mortgage debt is substantially lower in Uruguay than in the other countries analyzed, while that rate is remarkable higher in the US than in all other countries. Uruguayan families face high active interest rates, and contrary to the case of investments, they can not borrow from abroad. Also, Uruguay lacks a credit market for education purposes like the one in the US or Chile. Another interesting result is that nearly one third of households is indebted for consumption purposes (durable and non durable goods) in Uruguay, Chile and the US, while this figure is near 20% in Spain.

The fact that in Uruguay the mortgage participation rate is low with respect to other countries, while housing tenure ranks in the middle, poses the question regarding alternative ways other than mortgage to acquire the main residence such as inheritances or gifts. Kotlikoff and Summers, (1981) and De Nardi, (2004) has pointed out the role of inheritances to explain the asymmetry observed in the wealth distribution. In Uruguay, nearly 19 percent of households inherit the main residence, while 3 percent has received it as a gift. This data will be used later to account for the sources of wealth and income heterogeneity in Uruguay.

Table 3 reports the allocation of household liabilities. Debt for purchasing the main residence is the most valuable debt, followed by debt for consumption purposes. In Uruguay, debt for acquiring main residence is held by 8% of population while this figure is 17% in Chile, 44% in the US and 24% in Spain. Another interesting finding is that debt for consumption motives amount to almost 40% of total liabilities in Uruguay, while this figure is at around 10% in the rest of the countries analyzed.

4 Income and wealth: a univariate analysis

Income distribution has been the main fundamental of the analysis of economic inequality throughout the 20th Century. Cross country comparisons indicate that countries in Latin America are among the most unequal of the world (Amarante, et. al., 2016). Uruguay is one of the least unequal in the region, while Chile ranks in the middle.

Although a strong relationship between income and wealth is expected, recently available data on wealth has shown that studying only income distribution provides a partial and incomplete picture of economic inequality. For instance, Cowell et al. (2017) analyzes the wealth distribution of five developed countries (Finland, Italy, Sweden, the UK and the US) and they strikingly find that Sweden is ranked as one of the most unequal countries in terms of wealth, while this is not the same for income.

In this section, we analyze separately univariate distribution of income and wealth for Uruguay, Spain, Chile and the US. We report descriptive statistics for both distributions and provide commonly used indicators to assess for inequality.

Following the literature, to measure household wealth we consider net-worth, defined as the difference between total assets and total liabilities described in the previous section. To measure household income we consider the sum of all revenues retrieved by household from both sources, labor and capital.

As mentioned before, for all the countries analyzed except for Spain, income is considered after tax. The Chilean EFH and the Uruguayan EFHU collect information on after tax income directly, while the SCF and the EFF collect before tax income. For the SCF, we use the available TAXSIM program to compute taxes paid by households in the US, hence a measure of after tax income is considered for that country. By considering after tax income, we are acknowledging for a measure of "disposable" income and thus a compatible definition for income and wealth (Kennickell, 2009).

Table 4 reports the main descriptive statistics for wealth distribution. The top panel of the table shows the proportion of households with positive, null and negative net wealth. Around 80 percent of households have positive wealth in Uruguay and Chile while this figure is close to 90 in Spain and the US. Notice that the proportion of indebted households is similar in Uruguay, Chile and the US, but it is almost twice the figure in Spain. As expected, the number of "hand to mouth" consumers are larger in Uruguay and Chile (the developing economies) than in Spain and the US.

In Uruguay, mean wealth is at around USD 90,000, while the median is close to USD 35,000, the 10^{th} percentile is USD -357, and the 75^{th} and 90^{th} percentiles are USD 88,704 and USD 186,332 respectively. As expected, figures are closer to that of Chile, than to the other countries. In Chile median wealth is at around USD 30,000 and the mean is USD 74,725. Uruguayan figures are even closer to those of Chile if wealth from business is withdrawn from the analysis. In that case, the mean in Uruguay is USD 78,615, while the 75^{th} and the 90^{th} percentiles are USD 86,258 and USD 177,168 respectively. As expected, wealth is higher in Spain and in the US than in the developing economies under analysis.

Firstly, we provide estimations for the marginal distribution of income and wealth. Following Jäntti et. al, (2015) both variables are scaled by an inverse hyperbolic sine transformation, a function which is linear around zero and close to the logarithm when data is far from zero. The transformation deals relatively well with negative and zero values, while it also preserves data properties. Our results are similar to those of Jäntti et. al, (2015) (see figure 1): variations of wealth distribution across countries are substantially greater than those of income distributions and the distribution of wealth is bimodal (with a first mode at zero) and asymmetric. Also, wealth variance is remarkably larger than income variance. Hence, kernel density estimates show that wealth inequality is substantially greater than income inequality in all considered countries, but in particular in the US.

To confirm previous findings, we compute the Gini coefficient for income and wealth, a commonly used indicator to assess for income inequality (table 5). The coefficient is computed firstly considering the household as the unit of measure and later using per capita household income and wealth since household structure is important at the time of assessing for inequality, especially when considering developing economies in which numerous households could be more frequent among the poorest.[5] As expected, when considering income, the largest Gini coefficient is registered in Chile, while the smallest

[5]Notice, however, that as Cowell and Van Kerm (2015) point out there is still controversy about the application of equivalence scales to compute wealth in per capita terms.

is in Spain. Gini coefficient for income is smaller in Uruguay than that in the US. Notice that in the case of the US, the index is higher than one computed using Census or OECD data. This result may be due to the ability of the SCF to capture the top 1% of income distribution and also revenues from capital (Guner et al., 2014). Besides, Census data is top censored, which may lead to lower estimates of the Gini coefficient in comparison with data from the SCF (Guner et. al, 2014; Burkhauser et al. 2011).

We report in table 6 some additional indicators to assess for income inequality. The mean to median ratio is 1.3 in Uruguay, 1.36 in Spain and at around 1.7 in Chile and the US. Table 6 indicates that income is much more concentrated in Chile than in the other countries analyzed. Also, income is slightly less concentrated in Uruguay than in the US and similarly concentrated to that of Spain. Recall that income in Spain is before taxes; to the extent that taxes have an equalizer effect on income distribution, inequality measures of after tax income for Spain may indicate indeed a less unequal income distribution (OECD, 2012).

Wealth distribution, however, depicts a different picture. Gini coefficient is remarkably higher in the US than in the rest of the countries analyzed, while it is lower in Spain. In Chile and Uruguay, the Gini coefficient remains between the US and Spain [6]. The Gini coefficient can be graphically depicted in Lorenz curves (figure 2), in which both income and wealth are included. Income is less concentrated than wealth as the curve for income is closer to the Lorenz curve that would apply under perfect equality. Such a result is observed also in 13 of the 15 European countries analyzed in Cowell and Van Kerm (2015), Slovakia and Slovenia being the exceptions. Another interesting characteristic observed for all the countries, except for Spain, is that the bottom 30% of the population owns negative wealth (i.e. net debtors), thus the Lorenz curve goes below the horizontal axis.

The “mean/median" ratio for wealth is near 2.5 in Uruguay and Chile, while this figure is at around 6.5 in the US and 1.7 in Spain. This reflects a right-skewed distribution with a long right tail in which the mean is closer to the 75^{th} percentile than to the median. The ratio $75^{th}/25^{th}$, another measure accounting for dispersion, is at around 30 in Chile and the US. In Uruguay this ratio is close to 100, mainly because the 25^{th} percentile is lower than for the rest of the countries analyzed. On the other hand, the ratio for Spain is 4.5, well below the same indicator for the other countries (table 4).

Finally, we compute the concentration ratios defined as the proportion of income and wealth held by percentiles of the population (table 7). Along with previous findings, wealth is much more concentrated than income in all the countries analyzed (Kennickell, 2009; Bover, 2010; Arrondel et al. 2014). In a cross-country comparison, wealth is much more concentrated in the US than in the other countries, as for instance, the 20% of richest households owns almost 87% of total wealth. Spain remains as the country in which wealth is less concentrated, while concentration is quite similar in Chile and

[6] Despite wealth taking negative values, the Gini coefficient is well defined. However, it is possible for the index to take a value greater than 1, thus comparisons of the Gini coefficient between income and wealth must be taken carefully (Chen, et al., 1982)

Uruguay.

5 The joint distribution of income and wealth: Methods

Along with previous literature, the analysis made in the last section unveils a different picture for income and wealth (Cowell, et. al., 2017; Jäntti et. al, (2015)). However, in this case we account for evidence on developed and emerging economies. Chile is the country where income seems to be more unequally distributed, while Spain remains in the opposite side (recall that Spanish income is reported before taxes). Wealth distribution, however, seems to be more concentrated in the US than in the rest of the economies under analysis. Wealth also appears to be similarly distributed in Chile and Uruguay, despite income being much more concentrated in the former than in the latter.

A natural first step to analyze the relationship between income and wealth is to compute the Pearson and Spearman's ρ indexes. The Pearson index measures the linear correlation between both variables using cardinal data, while the Spearman's index exploits ordinal information and evaluates the association between individual rankings within the distributions of income and wealth. As Jäntti et. al, (2015) points out that an advantage of Spearman index, in the case under study, is that it is less sensitive to outliers (which can exert a strong influence on Pearson correlations). In addition, to study the relationship between rankings instead of monetary figures it is particularly appealing to proceed with cross-country comparison.

Although the analysis based on single indexes is useful, it is unable to capture the complexity of the relationship between income and wealth. Aiming to explore the full dependence of both variables, we construct copulas for the joint distribution of income and wealth as Kennickell (2009) or Jäntti et al., (2015). However, in a different vein, we estimate kernel smoothing copulas, an alternative to the purely empirical approach of Kennickell (2009) and to the fully parametric approach of Jäntti et al. (2015). Afterwards, we perform a non-parametric test for the hypothesis of equality between copulas of each pair of countries.

5.1 Non-parametric estimation of copulas

A copula is a joint distribution with uniform margins which allows one to observe the full dependence structure of different random vectors (Chen and Huang, 2007). The estimation of copulas is not the unique way to assess for the joint distribution of two variables and their degree of dependence, however they allow one to analyze the full dependence structure, which may not be well captured, for instance, by single summary statistics (Jäntti et al., 2015). This could be the case of income and wealth, as their marginal distribution has their own specificities.

In a different approach to that of Jäntti et al., (2015), who estimates parametric Plackett copulas for the joint distribution of income and wealth, copulas estimated in this paper are non-parametric. Notice that the Plackett copula is a single-parameter specification that is one-to-one related with Spearman's ρ index. The main advantage of estimating non-parametrically copulas is that it is model free, thus we do not assume any parametric model, neither for the marginal distributions of income and wealth nor for the copula.

First, we obtain purely empirical copulas as in (Kennickell, 2009). Let us consider $X = (X_1, X_2)$ a random vector and F a distribution function with marginal distributions F_1 and F_2; a copula can be defined as a bivariate distribution function C on $[0,1]^2$ such that:

$$F(x_1, x_2) = C\{F_1(x_1), F_2(x_2)\} \tag{1}$$

We construct purely empirical copulas by computing the relative frequency of households located in different quantiles of the joint distribution of income and wealth. More formally, the empirical copula can be described as:

$$C\{\hat{F}_1(x_1), \hat{F}_2(x_2)\} = \frac{1}{N+1} \sum_{i=1}^{N} \mathbb{1}(X_{1,i} \leq x_1, X_{2,i} \leq x_2) \tag{2}$$

Figure 3 depicts densities of the empirical copulas in which we divide income and wealth distribution in 10 percentiles. The colour scale indicates the magnitude of the joint density. Along with previous findings, in all the countries analyzed it is possible to notice a sharp peak located at the top 10% of both income and wealth distribution, while a smaller peak can be seen in the opposite pole of the joint distribution (Kennickell, 2009). A flatter density is located in the remaining areas of the distribution of income and wealth.

The construction of purely empirical copulas relies on ranking the observations and building the inverse function at some points of the distribution which are chosen arbitrarily.The estimation of copulas involves a first step estimate for every marginal distribution of the underlying random vectors, which are afterwards plugged in to estimate the multivariate distribution.

Aside from being a flexible model free approach to estimate non parametric densities, the kernel estimator is more efficient than the purely empirical approach and provides a more clear depiction of the graph making the copula visually "readable" and hence comprehensible.

Therefore, in this paper we provide smoothed kernel estimators for the empirical copula density. More formally our estimates are based on the following formula:

$$\hat{c}(u, v) = \frac{1}{Nh^2} \sum_{i=1}^{N} \mathbb{K}\left(\frac{u - \hat{F_{x1}}(X_{1i})}{h}, \frac{v - \hat{F_{x2}}(X_{2i})}{h}\right) \tag{3}$$

where $\hat{c}$ is the estimated copula density on u and v (pseudo-observations from the uniform marginal distributions), $\mathbb{K}$ is a primitive for $K : R \to R, \int K = 1$ and h is the kernel bandwidth. We take Gaussian functions for $\mathbb{K}$ for simplicity, although other functions can also be used to estimate the copula (see e.g. Charpentier et al., 2006). We use a bandwidth of 0.045.[7]

Moreover, addressing the well known “boundary bias” of the kernel estimator for copulas is especially important in the case of income and wealth, since major dependence between both variables is seen near the boundaries at the top and the bottom of the joint distribution. To deal with the “boundary bias” we use the “Mirror Image” technique (Deheuvels and Hominal, 1979; Schuster, 1985) consisting of adding observations using the “reflection” principle (see Appendix).

5.2 Testing equality between copulas

In this section we test the hypothesis of equality between copulas. Notice that it could be interesting to use the kernel densities estimates presented in the previous section to develop a formal test for the hypothesis of equality between copulas. However, to the best of our knowledge, there is no such test available in the literature. Thus, we follow the Rémillard and Scaillet (2009) non-parametric test.

As in the copula construction methods, building the test statistic relies on the estimation of rankings of individuals in each marginal distribution. Intuitively speaking, the statistic compare the pattern of concordances among individual rankings within the marginal distributions of two or more random variables between two populations.

Let us define the ranking of each individual in the marginal distribution of each l random variable in a m population as,

$$Um_{il} = \frac{N_m}{1+N_m} F_{l,m}\left(X_{il}\right) \quad \begin{array}{c} i = 1, ..Nm \\ l = 1, ..K; \quad K \geq 2 \\ m = 1, 2 \end{array}$$

where N_m is the size of population m, $F_{l,m}\left(X_{il}\right)$ denotes the cdf of the random variable l in population m evaluated at X_{il}.
To obtain the statistic we first compute the sample analogous of Um_{il} defined as,

$$\widehat{U}m_{il} = \frac{rank\left(X_{il}\right)}{1+N_m} \quad \text{with } rank\left(X_{il}\right) = \sum_{j=1}^{N_m} \mathbb{1}\left(X_{il} \geq X_{jl}\right)$$

The null hypothesis is that two copulas (m=1,2) are equal, and the test statistic proposed by Rémillard and Scaillet (2009) is based on the Cramér-von Mises principle and given

[7]Notice that optimal bandwidth is still an issue to kernel estimation of copulas

by:

$$S = \left(\frac{1}{N_1}+\frac{1}{N_2}\right)^{-1} \times \left\{ \begin{array}{c} \frac{1}{N_1^2}\sum\limits_{i=1}^{N_1}\sum\limits_{j=1}^{N_1}\prod\limits_{l=1}^{K}\left(1-\widehat{U}1_{il}\vee\widehat{U}1_{jl}\right) \\ +\frac{1}{N_2^2}\sum\limits_{i=1}^{N_2}\sum\limits_{j=1}^{N_2}\prod\limits_{l=1}^{K}\left(1-\widehat{U}2_{il}\vee\widehat{U}2_{jl}\right) \\ -\frac{2}{N_1N_2}\sum\limits_{i=1}^{N_1}\sum\limits_{j=1}^{N_2}\prod\limits_{l=1}^{K}\left(1-\widehat{U}1_{il}\vee\widehat{U}2_{jl}\right) \end{array} \right\}$$

where $a \vee b$ stands for $max(a,b)$.
The distribution of the test statistic are obtained via simulation. Let's define $\widetilde{S}_j$ as the value of the test statistic in the *j-th* replication. The p-value of the test is obtained as,

$$\frac{1}{J}\sum_{j=1}^{J}\mathbb{1}\left(\widetilde{S}_j > S\right).$$

In this paper we apply this test for a bivariate case (K=2), where income and wealth are the two variables of interest. We perform the test with two alternative goals: (i) compare the dependence structure between income and wealth across the four considered countries, (ii) analyze whether some household characteristics influence the observed pattern of dependence between income and wealth in Uruguay.

The application of the test in this case is not problem free. First, the sample size of the Monte Carlo simulations provided by Rémillard and Scaillet (2009) are considerably smaller than those of the surveys we are analyzing. Second, we have to acknowledge for the stratified design of the surveys under analysis by using weights in the test formula. Finally, to simulate the distribution for the test statistic, we follow these authors and draw univariate and independent standard normals for each margin but our results will probably be improved by considering alternative distributions (e.g. mixture models using Singh-Maddala as in Jäntti et al., (2015)).

6 Results

In this section we first analyze the evidence about the dependence structure between income and wealth in the four countries using the synthetic indexes and the results of the non-parametric estimation of copulas described above. Also, we perform the Rémillard and Scaillet (2009) test for equality between copulas to formally compare each pair of countries. Afterwards, we explore the determinants of income and wealth and give some insights about the influence of those factors over the observed pattern of dependence between these variables in Uruguay.

6.1 Pearson and Spearman's correlation indexes

Measured by the Pearson index, the correlation between income and wealth in the US attains 0.54, the highest among the countries under analysis (table 8), while the lowest correlation is observed for Uruguay (0.25). The correlation in the US exhibits the largest ranking correlation (0.6) and Chile the lowest one (0.28). Meanwhile, linear correlation is greater than ranking correlation in Chile and Spain, but the opposite is observed in the US and Uruguay. We also compute indexes for Uruguay excluding wealth for business in order to compare the results with those of Chile. Results indicate that for Uruguay, the linear correlation is greater when business are excluded while rank correlation almost does not change. In the case of Spain (using the 2011 wave of the EFF) our estimates are well above those of various previous studies (e.g. Jäntti et al., 2015; Arrondel et al., 2014) that use the 2008 wave of the Spanish survey.[8]

Table 8 also shows an indicator of the dependence of income and wealth at the bottom and top of the distribution. The QI1&QW1 statistic is defined as the proportion of households that simultaneously belong to the bottom quintile of income and the bottom quintile of wealth. QI5&QW5 is analogous but defined for the top quintiles. Notice that in absence of dependence between income and wealth, the proportion of households in the QI1&QW1 and QI5&QW5 would have been at around 0.04. Again, these statistics clearly capture a dependence between income and wealth and unveil that this dependence is stronger at the top than at the bottom of the distribution; and the US appears as the country with the strongest relationship between both variables.

6.2 Income and wealth copulas: a cross-country analysis

Figure 4 depicts the smoothed kernel copulas for the countries considered. Smoothed kernel estimates show that the relationship between income and wealth is very complex and asymmetric for all the countries considered. Previous results highlight the fact that such type of dependence pattern would not be captured by a model with a single parameter, pointing out the advantages of using non-parametric techniques to capture the dependence between the variables.

Concerning results from kernel estimates, as was the case for the no smoothed versions, it is possible to notice the highest peak at the top of the joint distribution and a "smaller" one close to [0,0] in the unit square. This reveals that top income households are among the wealthiest, while low income households are more likely to have low wealth in all the countries analyzed. The peak at the top of the joint distribution is remarkably higher and sharper in the US than in the other countries analyzed.

The kernel estimated copulas for Chile, Spain and Uruguay are very similar, while that of the US looks very different, in particular the sharp peak at the [1,1] corner is considerably larger than in the other three countries. To improve the visualization of the differences

[8] That change could be rationalized by the strong impact of the recent Spanish economic crisis on the distribution of income and wealth.

between estimated copulas for Uruguay and the other countries we graph those differences in Figure 5. The value of those graph are given by the simple difference between the estimation of the density copula for the "other" country and that for Uruguay at each point. Those graphs also suggest that the pattern of dependence between income and wealth is similar in Chile, Spain and Uruguay, but remarkably different in the US. However, these results do not prove formally that copulas are statistically similar/different. To this end, in the next section we proceed to formally test the former hypothesis by using a non-parametric test of equality between copulas.

Table 9 includes the p-values from the Rémillard and Scaillet (2009) test using one thousand replications for each pair of countries. The hypothesis of equality between copulas is rejected in all cases, but for the pair Spain and Uruguay.

Results from the test unveils an interesting picture when performing the cross-country comparisons. Firstly, the copulas may look similar at a glance. A formal test may help to assess for differences between them and hence for the dependence between both variables. Secondly, notice that Spearman's correlation for Uruguay and Spain are also close to each other (0.37 and 0.4 respectively). Finally, when analyzing the marginal distribution for both variables, measures for income distribution are quite similar in Spain and Uruguay, even when income and wealth are considerable higher and more equally distributed in Spain than in Uruguay.

6.3 Sources of heterogeneity and their influence on the dependence between income and wealth in Uruguay

The analysis made in the previous section reveals that income and wealth are linked and that dependence between both variables is stronger at the top and at the bottom of the joint distribution. The literature on household savings and capital accumulation has pointed out different factors shaping the marginal distributions of both variables. For instance, life cycle has been proved important for wealth accumulation, while it is also important to model its distribution across households (see e.g. Hugget, 1996). Also bequest motives play a key role for explaining accumulation process and cross-sectional wealth distribution (Kotlikoff and Summers, 1981; De Nardi, 2004).

However, we still do not know which are the main sources of heterogeneity driving the relative position of households in the distribution of income and wealth, and which is the degree of dependence between both variables when factors such as age or education are taken onto account. To shed light into this problem, Arrondel et al. (2014) estimates generalized ordered probit models for EU countries to link the household position in wealth distribution to that of income. They also considered different factors such as age profile of household members or inheritances which also affects household income and wealth.

In this paper, we follow a different approach to that of Arrondel et al. (2014). We estimate mean regressions taking income and wealth as dependent variables to analyze the main sources of heterogeneity. Still, we do not include wealth as a covariate in model for income and viceversa. Instead, to assess for the dependence between income and wealth when other factors are considered we build smoothed kernel copulas using the residuals from income and wealth mean regressions. Afterwards, we compare the copulas of the residuals with that of the observed income and wealth and perform the Rémillard and Scaillet (2009) test for equality between those copulas.

We first estimate a set of mean regressions considering separately each potential source of heterogeneity, including life cycle (using a quadratic on average age of households members aged 18 or older), family composition (including the number of household members, a dummy for the presence of children under 16 years old at home and the family structure distinguishing couple, single male, single female without children and single female with children), education (years of schooling of the reference person); inheritances (dummies indicating that main residence, other real estate or business were inherited) and region (a dummy for residence in Montevideo). Afterwards, we sequentially add every group of covariates.

All groups of covariates result statistically significant for both wealth and income (see tables 10 and 11). Some interesting conclusions arise from the comparison among the estimated R-squared. First, our data confirm the well known fact that education is a major determinant for income: It explains 31 per cent of total income variance. Years of schooling reveals to be also significant for wealth, but its explanatory power on this variable is substantially smaller (R-squared is 0.08). On the other hand, inheritances are the main determinant for wealth within the considered sources of heterogeneity, and explain 15 percent of this variable's variance. Inheritances also influence income but their explanatory power is low (3.6 per cent).

Concerning regressions that include simultaneously all covariates, the R-squared estimates are 0.41 for income and 0.23 for wealth. Recall that by including only inheritances the R-squared of the model for wealth is 0.15. These results suggest that wealth's heterogeneity is hard to explain by using the set of household characteristics commonly used as determinants of income.

We find that education and inheritances are the main sources of heterogeneity of income and wealth, but life cycle and the family structure also play a role. To analyze the average partial effects of each covariate we use the regressions that include all variables. Years of schooling is significant for both income and wealth, its influence on income being greater in magnitude than that of wealth: the average partial effect of an additional year of schooling is 9.7% for income and 1.4% for wealth.

Inheritances of real estate (which are not the main residence) and business have a strong and positive impact on wealth. Having inherited the main residence has a positive impact (significant at the 5% level) on wealth. Average wealth of households which had inherited other real estate is 23% higher than that of households who had not. Similarly, inheritances of business increase mean wealth by almost 32%. The influence of inheritances on the estimates for income are mixed. The inheritance of other real estate and business affects positively the average income but the mean income of those who had inherited their main residence is lower than those who had not.

The effect of age over net wealth is significant at the 10th percent level and positive (age squared is not significant) while life cycle effect is present for average income. Average income and wealth increase with the number of household members, although the effect on income is sharper. Also, mean income is higher for couples than for singles. Meanwhile, average wealth of couples and single men households are greater than that of single females. Finally, average income and net wealth are lower when children under 16 years old are living in the household.

To assess for the joint distribution of income and wealth when these factors are taken into account, we estimate empirical copulas using the residuals of the univariate mean regressions for income and wealth (figure 6). In addition, figure 7 plots the differences between copulas of residuals and observed variables.

We find that education is the covariate with the highest influence on the dependence between income and wealth. Actually, the evidence from the test of equality between copulas reveals that, among the covariates considered, education is the only one which significantly influences the shape of the copula (see table 12).When removing the effect of education, the dependence between income and wealth at the [0,0] corner vanishes, while the strong dependence observed at the [1,1] corner is reduced.

The test suggests that the other factors are not statistically significant to explain the shape of the copula. However, it is interesting to analyze some observed differences between the copulas that consider the influence of those variables. By removing the life cycle influence, the peak at the bottom is smoothed but the peak at the top becomes slightly sharper. Also, the family structure and inheritances play a role, since less-wealthy families are also those with the lowest income. In addition, by addressing the differences between regions we can conclude that households at the extremes of the bivariate distribution are more frequent in Montevideo (the capital city) than in the rest of the country.

Finally, we consider the residuals of regressions that include all covariates. The corresponding copula is statistically different and flatter than that of the observed income and wealth. The Rémillard and Scaillet (2009) test indicates that education drives this result. Besides, the copula of the residuals do not exhibit the peak at the bottom of the joint distribution. The peak at the top is also reduced, but still relevant in magnitude; bringing evidence that the strong correspondence between high wealth and top income households can be only partially explained by the considered household characteristics.

Thus, we can conclude that household characteristics that are usually used to study income heterogeneity has little explanatory power for analyzing both wealth and its relationship with income. Note that this conclusion is similar to those obtained by other authors who use substantially different approaches to ours (Arrondel et al., 2014; Cowell et al., 2017; Jäntti et al., 2015).

7 Concluding Remarks

In this paper we analyze income and wealth distribution in Uruguay, while we compare it to that of Chile, Spain and the US. We use data from surveys of finances and wealth with similar characteristics allowing for cross-country comparisons. An interesting finding is that non financial assets account for a larger fraction of total household assets in Chile and Uruguay than in Spain and the US. This is not surprising when considering that in developing economies, financial markets are shallow while households are also less financially included than in the developed economies.

As expected, wealth is more concentrated than income in all the analyzed countries. However, the analysis of income and wealth distribution reveals that in Chile and Uruguay, wealth seems to be less concentrated than in the US, but more concentrated than in Spain. This is not the case for income, which is more concentrated in Chile than in the US.

We assess for the dependence between income and wealth by building non-parametric kernel smoothed copulas. The non-parametric estimation is model free, which is strongly recommended to capture the complex and asymmetric nature of the dependence structure of income and wealth. As expected, we find that low income households are more likely to have less wealth, while top income households are among the wealthiest, being the peak at the top more than twice that at the bottom. This result is observed in all the countries under analysis.

Copulas for Chile Spain and Uruguay look similar, while that of the US exhibits a sharper peak in the top of the joint distribution. However, the cross-country comparison is not an easy task. In further analysis, we formally compare copulas by performing the non-parametric test of equality between copulas proposed by Rémillard and Scaillet (2009). We consider every pair of countries and find that the hypothesis of equality between copulas is rejected in all cases, except for the pair Spain-Uruguay.

Since income and wealth are both affected by household characteristics, we also estimate for Uruguay, mean regressions for income and wealth. We include as covariates some factors which are well known as determinants of income such as life cycle, education or family structure, but we also add covariates indicating whether households have received inheritances. Years of schooling, age profile of household members, the household composition and bequests are among the main sources of heterogeneity for income and wealth. We conclude that the set of covariates usually considered as determinants of income are also significant but, has little explanatory power for analyzing wealth. Years of schooling is the main source of heterogeneity of income, and also influences wealth, but inheritances have the highest explanatory power for wealth.

Finally, to assess for the joint distribution of income and wealth after removing the influence of these factors, empirical copulas using the residuals from the mean regressions for income and wealth are estimated. Our main finding is that education is relevant for both the marginal distributions and the dependence structure of income and wealth.

The evidence presented in this paper highlights the need for much more research concerning determinants of wealth and its relationship with income. Further analysis can be done in many directions. The most obvious one is to explore other household characteristics that are not of interest for income according the vast literature on that topic, but could play a role for explaining wealth. Finally, further methods to explore the differences between copulas may be developed.

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Table 1: Survey description

	EFF	EFHU	EFH	SCF
Country	Spain	Uruguay	Chile	US
Year	2011	2013-2014	2014	2013
Observations	6,106	3,490	4,502	6,015
Unit of analysis	Household	Household	Household	Household
Number of imputed datasets	5	10	30	5

Notes: Year corresponds to the year in which data was collected. The number of imputed dataset is the number of databases arising from multiple imputation.

Table 2: Participation rates for household assets and debts (% of households)

	Uruguay	Chile	Spain	US
Financial assets	**48.9**	**82.2**	**95.8**	**94.5**
Non-financial assets	**85.2**	**79.0**	**96.2**	**91.3**
Main residence	61.7	61.9	83.1	65.2
Other real estate	12.7	13.3	40.2	13.3
Own business	20.9	-.-	12.3	11.7
Vehicles	56.9	50.3	78.4	86.3
Art, jewerly, other	3.6	1.4	22.6	7.3
Debts	**44.5**	**72.6**	**49.3**	**74.5**
Main residence	8.0	17.0	26.6	44.5
Other real estate	1.2	3.5	9.5	5.3
Credit card	9.0	54.4	5.9	38.1
Consumption, vehicles	36.5	33.7	21.8	38.1
Education loans	-.-	8.2	-.-	20.0
Other debt	-.-	4.8	3.8	6.6

Notes: Participation rate is computed as the percentage of households owning each asset/liability. We take all the imputation sets for each survey. Sample weights were used in all cases.

Table 3: Allocation of household assets and liabilities (% of total assets/liabilities)

	Uruguay	Chile	Spain	US
Assets				
Financial assets	**4.5**	**9.2**	**15.1**	**40.8**
Non-financial assets	**95.5**	**90.7**	**84.8**	**59.2**
Main residence	55.2	63.4	49.6	27.6
Other real estate	23.4	19.7	24.2	6.8
Own business	12.2	-.-	7.77	20.8
Vehicles	4.5	6.8	2.39	3.1
Art, jewerly, other	0.2	0.8	0.83	0.7
Liabilities				
Main residence	52.3	58.4	62.4	73.7
Other real estate	9.2	15.2	24.3	8.9
Credit card	0.7	8.7	0.2	2.4
Consumption, vehicles	37.6	12.8	11.3	7.5
Education loans	-.-	3.6	-.-	6.3
Other debt	-.-	1.3	1.6	1.0

Note: Each asset share is computed as the proportion of each item in total assets value. Each liability share is computed as the proportion of each item in total debt value. We take all the imputation sets for each survey. Sample weights were used in all cases.

Table 4: Net wealth - Main descriptive statistics

	Uruguay	Chile	Spain	US
W $>$ 0	0.79	0.78	0.94	0.87
W $=$ 0	0.10	0.07	0.01	0.01
W $<$ 0	0.12	0.15	0.05	0.12
Mean	90,417	75,104	369,093	536,876
10^{th} percentile	-357	-559	8,549	-2,099
25^{th} percentile	857	2,498	93,205	8,924
50^{th} percentile	35,534	31,298	215,011	82,759
75^{th} percentile	88,704	75,993	414,357	320,763
90^{th} percentile	186,332	172,532	732,717	958,754
p 75^{th}/p 25^{th}	103	30.4	4.45	35.9
Mean /Median	2.54	2.39	1.72	6.5

Note: Figures are in 2014 USD. We take all the imputation sets for each survey. Sample weights were used in all cases.

Table 5: Gini coefficient: income and wealth

	Uruguay	Chile	Spain	US	Uruguay	Chile	Spain	US
	Wealth				Income			
Gini	0.75	0.74	0.60	0.85	0.42	0.53	0.44	0.53
Gini (per capita)	0.77	0.79	0.62	0.86	0.46	0.56	0.42	0.53

Note: For all countries except Spain we consider after tax income. Despite the presence of negative values, Gini coefficient for wealth is well defined, although is not bounded at 1 (Chen et al., 1982). Per capita Gini coefficients are computed using income and wealth divided between the number of household members. We take all the imputation sets for each survey. Sample weights were used in all cases.

Table 6: Income - Main descriptive statistics

	Uruguay	Chile	Spain	US
Mean	18,703	27,031	46,527	69,825
10^{th} percentile	5,004	4,841	11,572	13,577
25^{th} percentile	8,400	8,734	18,758	23,845
50^{th} percentile	14,400	16,041	34,161	40,976
75^{th} percentile	24,000	30,084	57,698	72,692
90^{th} percentile	36,078	56,098	88,078	120,881
p 75^{th}/p 25^{th}	2.86	3.44	3.08	3.05
Mean/median	1.30	1.69	1.36	1.70

Note: For all countries except Spain we consider after tax income. We take all the imputation sets for each survey. Sample weights were used in all cases.

Table 7: Concentration ratios (% of income and wealth)

	Uruguay	Chile	Spain	US	Uruguay	Chile	Spain	US
Percentiles	Wealth				Income			
0-20	-0.99	-1.78	0.57	-0.67	5.18	3.28	4.65	3.83
20-40	1.54	1.95	6.33	0.65	9.93	7.37	9.31	7.74
40-60	7.94	8.44	11.76	3.22	15.13	11.84	14.69	11.86
60-80	16.94	17.09	19.79	9.79	22.45	19.48	22.11	18.52
80-100	74.57	74.30	61.53	87.01	47.30	58.04	49.22	58.05

Note: For all countries except Spain we consider after tax income. We take all the imputation sets for each survey. Sample weights were used in all cases.

Table 8: Income and Wealth correlation

	Pearson	Spearman	QI1 & QW1	QI5 & QW5
Uruguay	0.25	0.37	0.069	0.096
Uruguay (without business)	0.29	0.36	0.069	0.096
Chile	0.37	0.28	0.053	0.094
Spain	0.51	0.40	0.060	0.089
US	0.54	0.60	0.089	0.121

Notes: For all countries except Spain we consider after tax income. We take all the imputation sets for each survey. Sample weights were used in all cases. QI1 & QW1 stands for the proportion of households within the bottom quintile of income and the bottom quintile of wealth. QI5 & QW5 is similarly defined for the top quintile.

Table 9: Rémillard and Scaillet test for equality between each pair of copulas (p-values)

	Uruguay	Chile	Spain
Chile	0.001		
Spain	0.195	0.000	
US	0.000	0.000	0.000

Notes: The null establishes that both copulas are equal. p-values are computed via simulation using 1,000 replications. Sample weights were used in all cases.

Table 10: Mean regressions. Dependent variable: net wealth (in logs)

Age	0.00817***					0.00673***	0.00598***	0.00384***	0.00380***
	[0.00151]					[0.00146]	[0.00142]	[0.00135]	[0.00136]
Age squared	-0.00599***					-0.00473***	-0.00273*	-0.00106	-0.00101
	[0.00145]					[0.00145]	[0.00143]	[0.00135]	[0.00136]
Number of hh's members		-0.00726***				-0.00142	0.00772***	0.00853***	0.00848***
		[0.00277]				[0.00282]	[0.00286]	[0.00277]	[0.00277]
Male		-0.0583***				-0.0529***	-0.0238	-0.0214	-0.0218
		[0.0153]				[0.0151]	[0.0148]	[0.0142]	[0.0143]
Female without children		-0.0617***				-0.0640***	-0.0575***	-0.0460***	-0.0461***
		[0.0127]				[0.0127]	[0.0123]	[0.0115]	[0.0115]
Female without children		-0.0878***				-0.0787***	-0.0536***	-0.0473***	-0.0480***
		[0.00850]				[0.00825]	[0.00866]	[0.00827]	[0.00825]
Children under 16 at home		-0.0461***				-0.0391***	-0.0294***	-0.0255***	-0.0241***
		[0.00894]				[0.00894]	[0.00866]	[0.00811]	[0.00822]
Years of schooling			0.0159***				0.0175***	0.0146***	0.0142***
			[0.00117]				[0.00130]	[0.00111]	[0.00108]
Main residence inherited				0.0232**				0.0278***	0.0285***
				[0.0111]				[0.0107]	[0.0107]
Other real estate inherited				0.280***				0.232***	0.232***
				[0.0308]				[0.0290]	[0.0290]
Business inherited				0.348***				0.320***	0.322***
				[0.0673]				[0.0654]	[0.0654]
Montevideo					0.0405***				0.0177**
					[0.00897]				[0.00802]
Constant	13.26***	13.57***	13.35***	13.48***	13.49***	13.34***	13.11***	13.17***	13.17***
	[0.0350]	[0.0149]	[0.0110]	[0.00469]	[0.00576]	[0.0339]	[0.0370]	[0.0339]	[0.0340]
R-squared	0.017	0.025	0.078	0.146	0.007	0.037	0.123	0.230	0.231
Observations	3,471	3,471	3,471	3,471	3,471	3,471	3,471	3,471	3,471

Note: Omitted category for family structure is couple. *, **, *** denotes significance at 10%, 5% and 1% level respectively. We use the 10 imputation sets provided in EFHU database and compute statistics following Rubin (1987) rules.

Table 11: Mean regressions. Dependent variable: income (in logs)

Age	0.0308***					0.0211***	0.0165***	0.0157***	0.0153***
	[0.00582]					[0.00569]	[0.00479]	[0.00481]	[0.00477]
Age squared	-0.0332***					-0.0235***	-0.0116**	-0.0109**	-0.0105**
	[0.00549]					[0.00544]	[0.00457]	[0.00457]	[0.00454]
Number of hh's members		0.0273***				0.0112	0.0659***	0.0672***	0.0665***
		[0.0102]				[0.0105]	[0.00916]	[0.00917]	[0.00918]
Male		-0.396***				-0.398***	-0.223***	-0.215***	-0.220***
		[0.0465]				[0.0465]	[0.0397]	[0.0395]	[0.0393]
Female without children		-0.461***				-0.421***	-0.382***	-0.369***	-0.369***
		[0.0391]				[0.0399]	[0.0335]	[0.0333]	[0.0330]
Female without children		-0.610***				-0.621***	-0.471***	-0.466***	-0.473***
		[0.0481]				[0.0480]	[0.0409]	[0.0412]	[0.0409]
Children under 16 at home		-0.194***				-0.208***	-0.150***	-0.147***	-0.131***
		[0.0305]				[0.0304]	[0.0254]	[0.0253]	[0.0252]
Years of schooling			0.105***				0.105***	0.102***	0.0970***
			[0.00265]				[0.00267]	[0.00270]	[0.00273]
Main residence inherited				-0.146***				-0.0932***	-0.0858***
				[0.0386]				[0.0321]	[0.0316]
Other real estate inherited				0.535***				0.228***	0.235***
				[0.0562]				[0.0467]	[0.0462]
Business inherited				0.376***				0.189**	0.211***
				[0.0982]				[0.0825]	[0.0814]
Montevideo					0.392***				0.203***
					[0.0277]				[0.0228]
Constant	11.98***	12.77***	11.54***	12.58***	12.45***	12.40***	11.02***	11.06***	11.03***
	[0.144]	[0.0372]	[0.0295]	[0.0152]	[0.0167]	[0.146]	[0.129]	[0.130]	[0.129]
R-squared	0.020	0.097	0.307	0.036	0.057	0.107	0.388	0.395	0.409
Observations	3,471	3,471	3,471	3,471	3,471	3,471	3,471	3,471	3,471

Note: Omitted category for family structure is couple. *, **, *** denotes significance at 10%, 5% and 1% level respectively. We use the 10 imputation sets provided in EFHU database and compute statistics following Rubin (1987) rules.

Table 12: Rémillard and Scaillet test for equality between two copulas (p-values)

Factor	Each factor[1]	Sequential[2]	Each added factor[3]
Age	0.197		
Family structure	0.332	0.214	0.960
Education	0.000	0.000	0.000
Inherintances	0.868	0.000	1.000
Region	0.340	0.000	1.000

Notes:

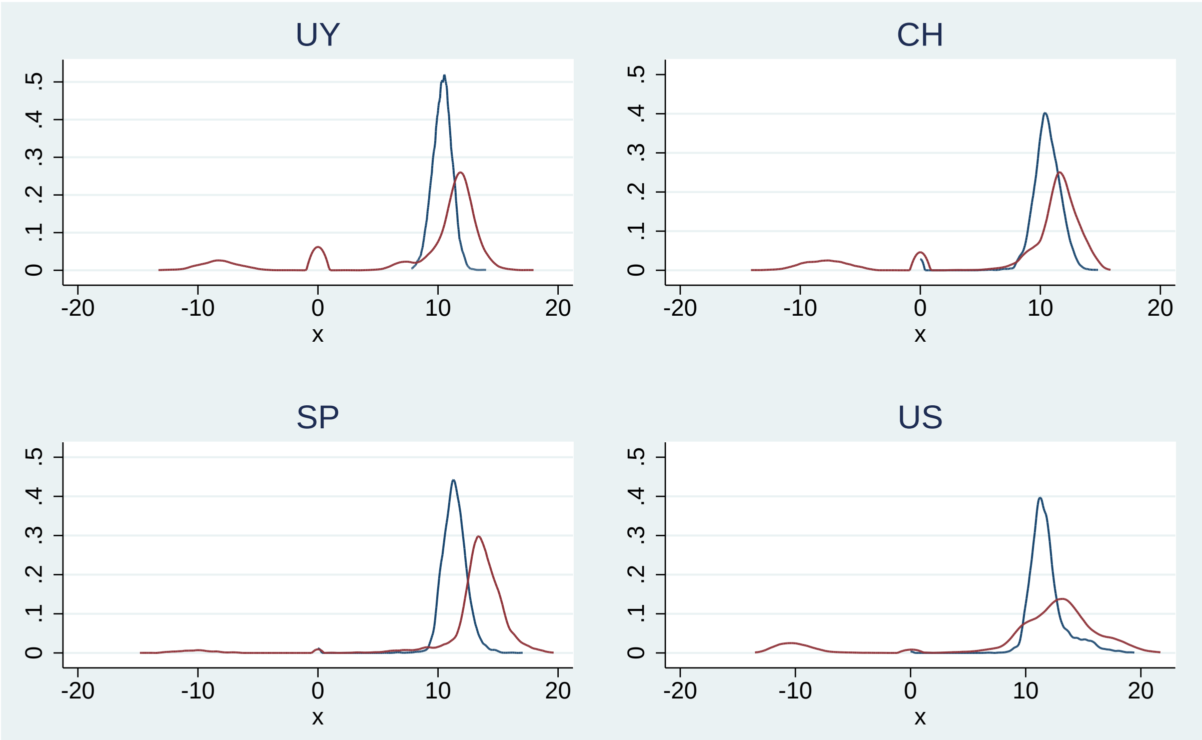
The null establishes that both copulas are equal. p-values are computed via simulation using 1,000 replications.

[1] Test of equality between copulas of observed income and wealth versus residuals from a regression that includes each factor;

[2] Test of equality between copulas of observed income and wealth versus residuals from regressions that sequentially add each factor;

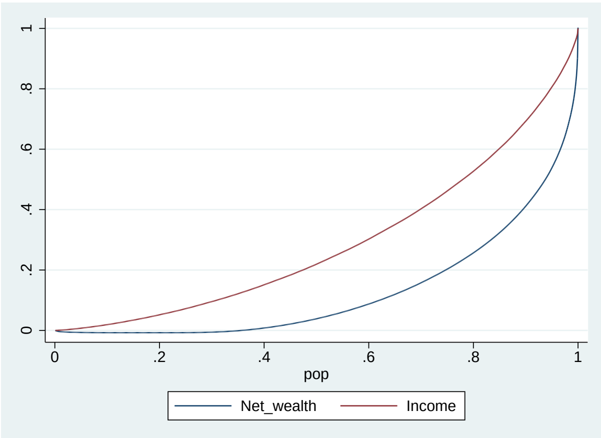
[3] Test of equality between copulas of residuals at each sequential step versus residuals of the previous one.

Figure 1: Kernel densities for income and wealth

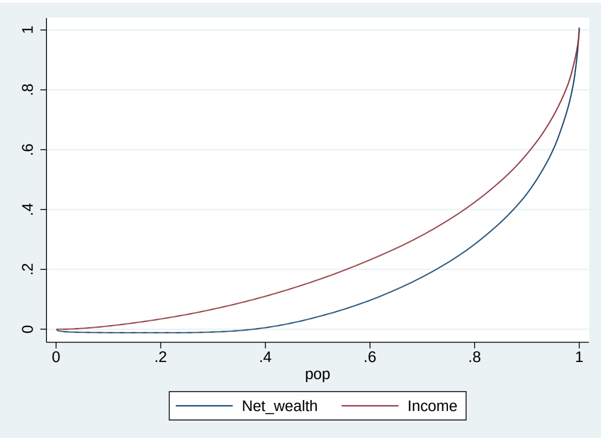


Note: x-scale is scaled by an inverse hyperbolic sine transformation

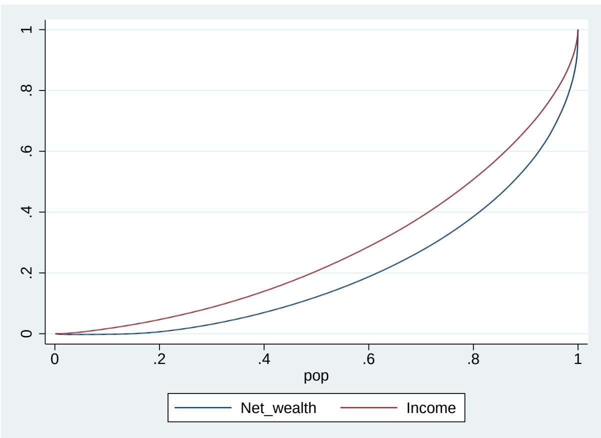
Figure 2: Lorenz curves for income and wealth



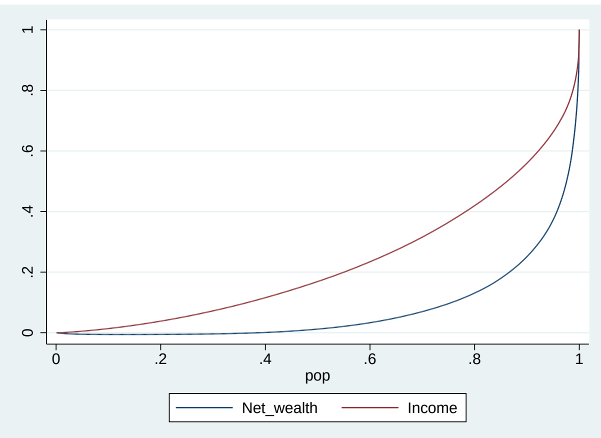
Uruguay



Chile



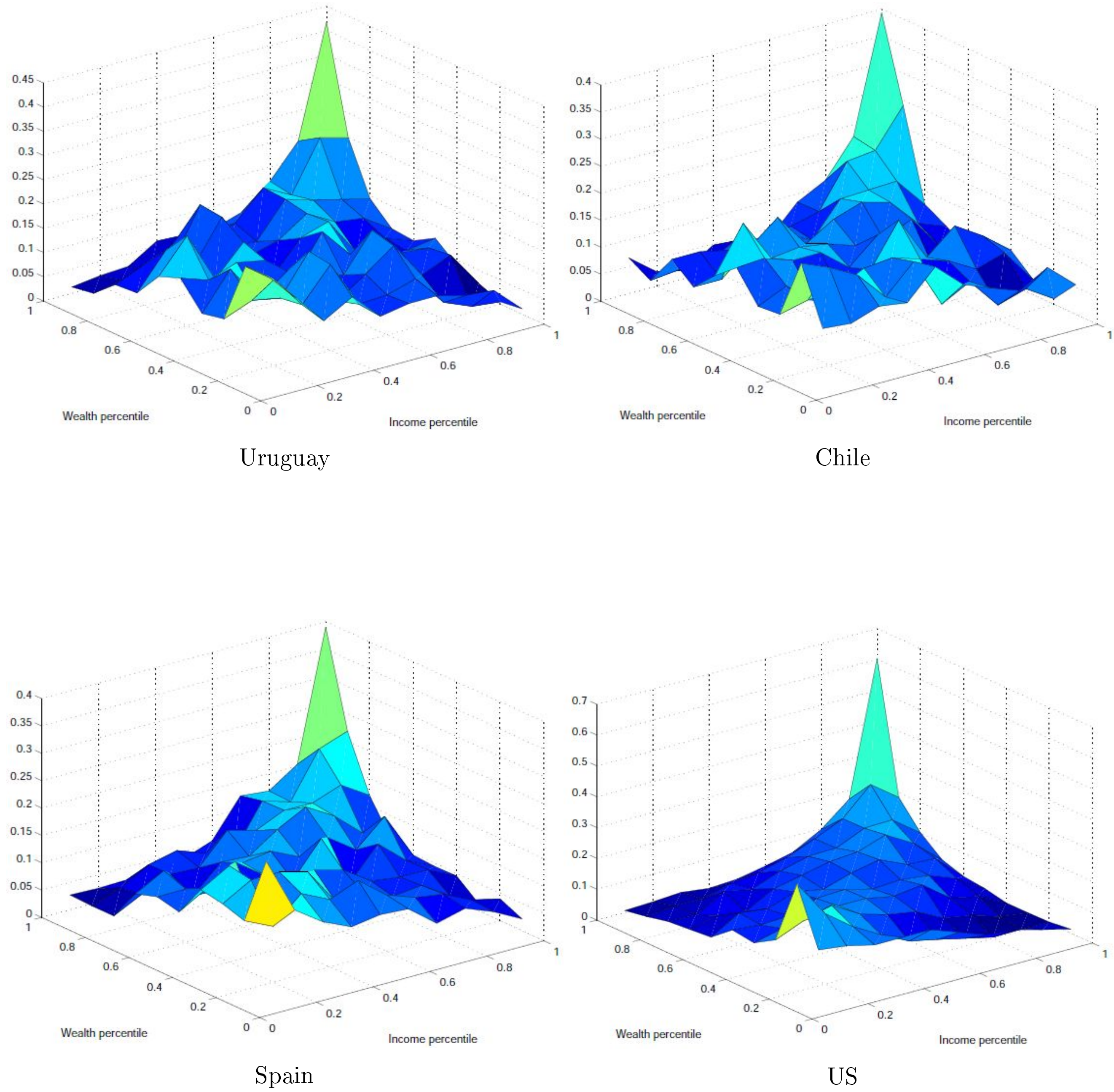
Spain



US

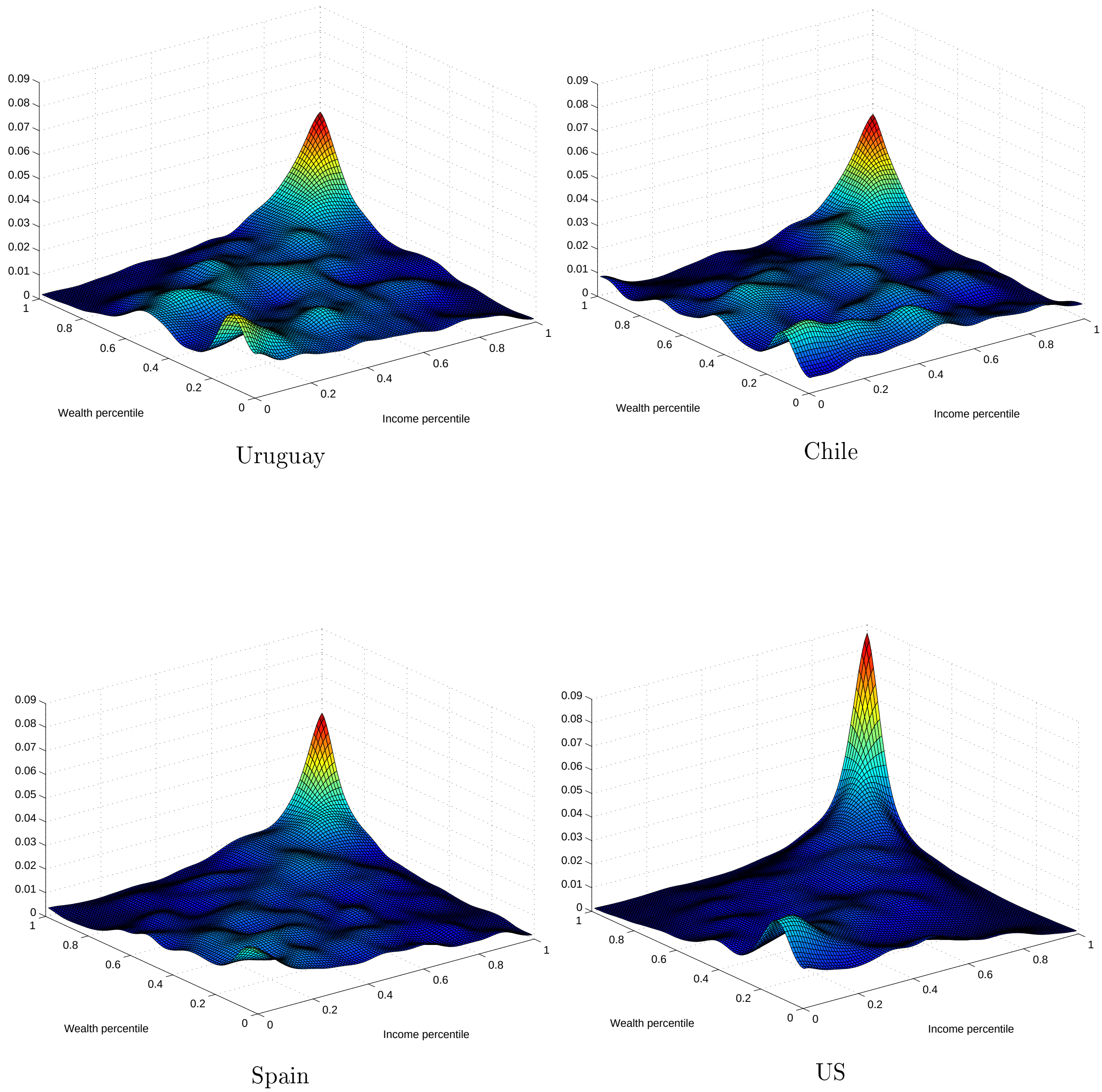
Note: Lorenz curves were built by computing the concentration ratios for each percentile of income and wealth. We take all the different imputed sets for each survey. Sample weights were used in all cases.

Figure 3: Empirical copulas for income and wealth



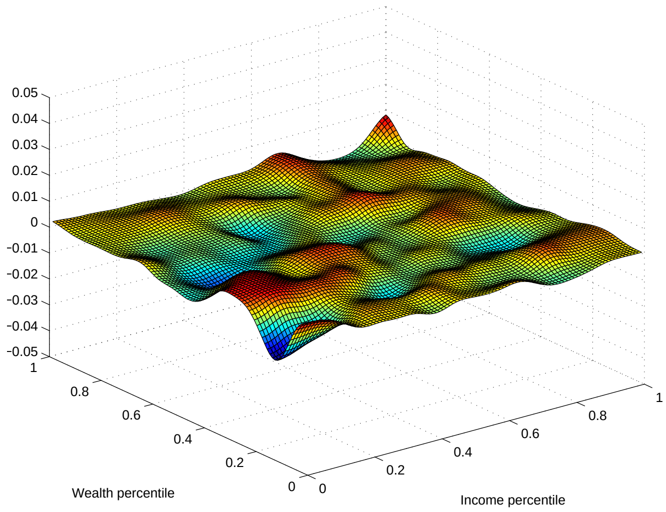
Note: Empirical copulas were built considering the proportion of households remaining in each quantile. We divide the sample in 10 percentiles of income and wealth. We take all the different imputed sets for each survey. Sample weights were used in all cases.

Figure 4: Kernel smoothed copulas for income and wealth

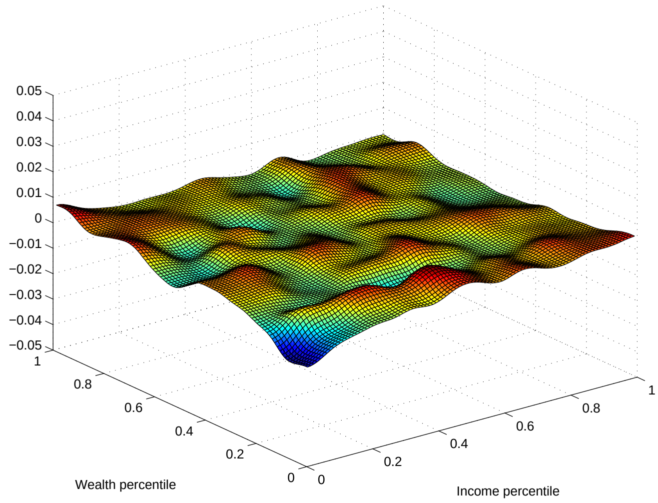


Note: Gaussian kernel copulas are built considering a bandwidth of 0.045. We take all the different imputed sets for each survey. Sample weights were used in all cases.

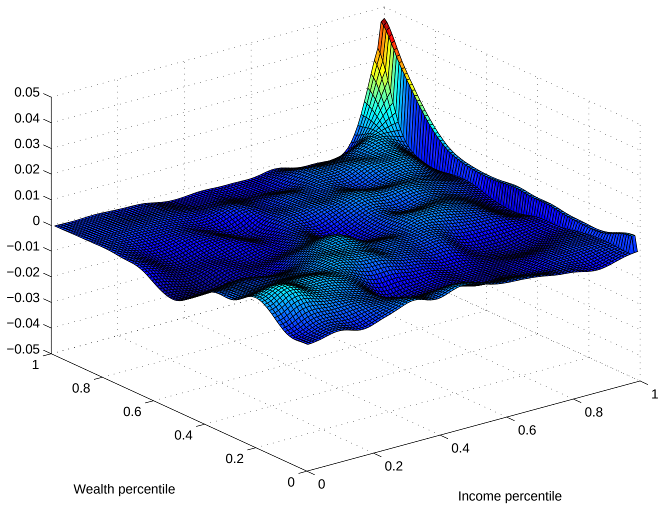
Figure 5: Chile, Spain and the US vs Uruguay: Differences between kernel estimated copulas



Chile minus Uruguay



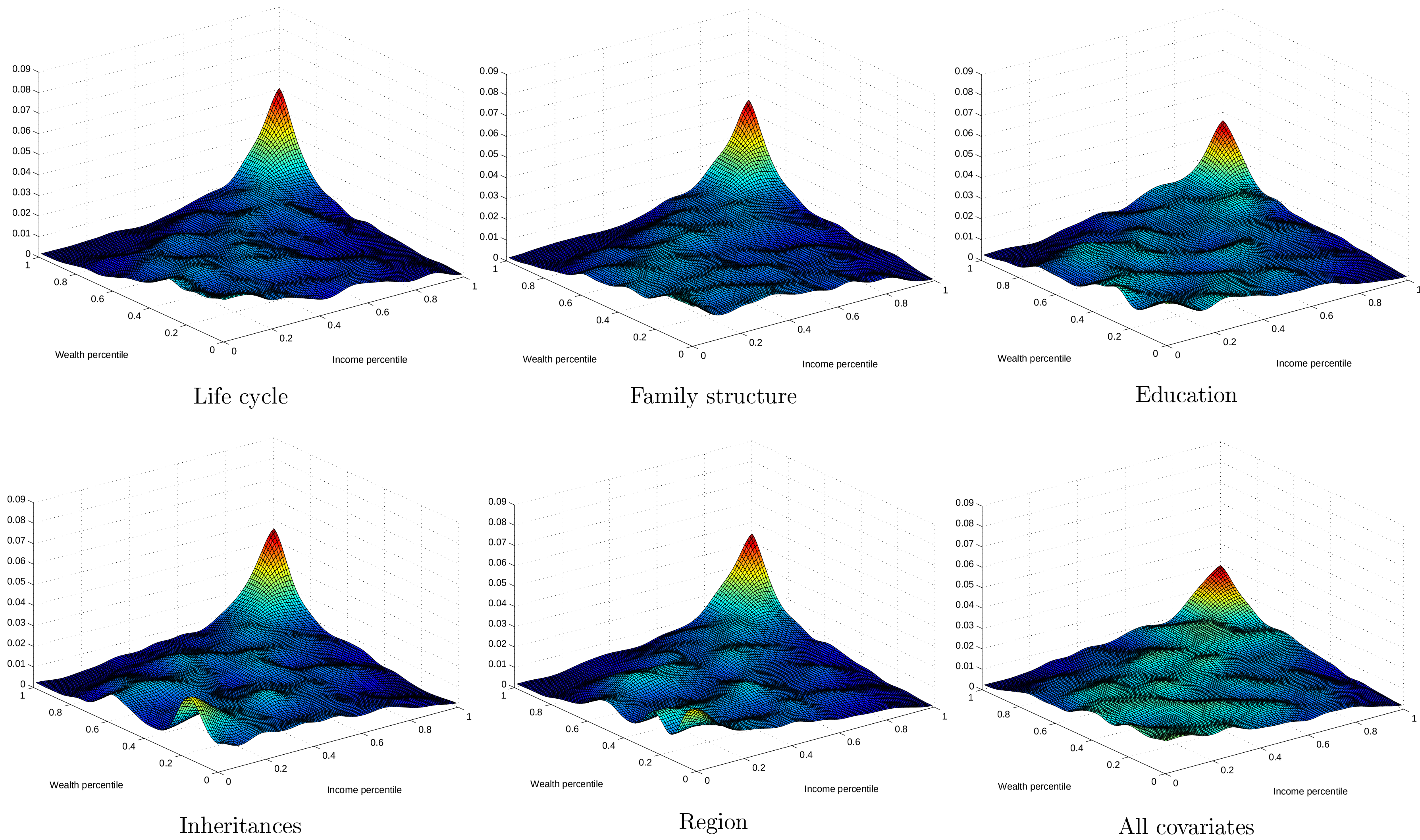
Spain minus Uruguay



US minus Uruguay

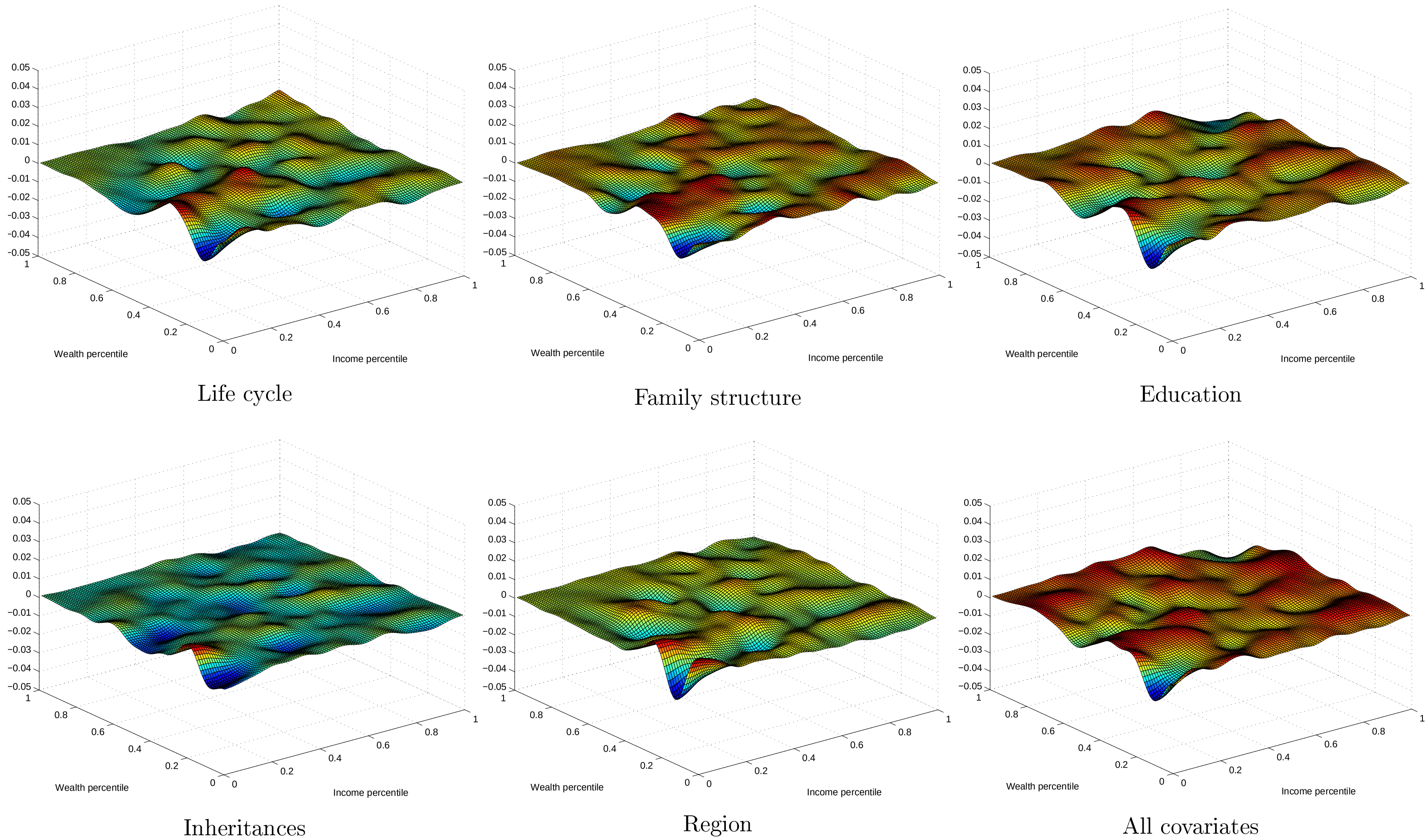
Note: Kernel copulas were built considering a bandwidth of 0.045. We take all the different imputed sets for each survey. Sample weights were used in all cases.

Figure 6: Kernel estimated copulas for residuals from income and wealth mean regressions



Note: Kernel copulas were built considering a bandwidth of 0.045. We take all the different imputed sets for each survey. Sample weights were used in all cases.

Figure 7: Observed versus residuals: Differences between kernel estimated copulas



Note: Kernel copulas were built considering a bandwidth of 0.045. We take all the different imputed sets for each survey. Sample weights were used in all cases.

Appendix

The "Mirror Image" technique to deal with the "boundary bias" in kernel estimators for copulas consists of adding probability mass by reflecting the sample with respect to each edge and corner of the unit square such that the bias is minimized.

In the bivariate case (income and wealth), a copula is the joint CDF of $F(x_1, x_2) = C(F_{x1}(X_1), F_{x2}(X_2))$. At the time of estimating the copula, the original dataset is converted to $(\hat{U}_i, \hat{V}_i) = C(\hat{F_{x1}}(X_{1i}), \hat{F_{x1}}(X_{2i}))$ for $i = 1, 2..., N$. Where empirical CDF are used to estimate the marginal distributions:

$$\hat{F_{x1}}(X_{1i}) = \frac{1}{N+1} \sum_{i=1}^{N} \mathbb{1}(X_{1,i} \leq x_1) \tag{4}$$

$$\hat{F_{x2}}(X_{2i}) = \frac{1}{N+1} \sum_{i=1}^{N} \mathbb{1}(X_{2,i} \leq x_2) \tag{5}$$

Following Charpentier et al., (2006), the "mirror image" technique consists of adding observations to reflect each point with respect to the edges and corners of the unit square. More formally, on adding: $(\pm\hat{U}_i, \pm\hat{V}_i)$, $(\pm\hat{U}_i, 2 - \hat{V}_i)$, $(2 - \hat{U}_i, \pm\hat{V}_i)$, $(2 - \hat{U}_i, 2 - \hat{V}_i)$ such that the kernel smoothed version for the copula density is:

$$\begin{aligned}
\hat{c}(u,v) = \frac{1}{Nh^2} \sum_{i=1}^{N} \Bigg[& \mathbb{K}\left(\frac{u-\hat{U}_i}{h}\right) \mathbb{K}\left(\frac{v-\hat{V}_i}{h}\right) + \mathbb{K}\left(\frac{u+\hat{U}_i}{h}\right) \mathbb{K}\left(\frac{v-\hat{V}_i}{h}\right) \\
+ & \mathbb{K}\left(\frac{u-\hat{U}_i}{h}\right) \mathbb{K}\left(\frac{v+\hat{V}_i}{h}\right) + \mathbb{K}\left(\frac{u+\hat{U}_i}{h}\right) \mathbb{K}\left(\frac{v+\hat{V}_i}{h}\right) \\
+ & \mathbb{K}\left(\frac{u-\hat{U}_i}{h}\right) \mathbb{K}\left(\frac{v-2+\hat{V}_i}{h}\right) + \mathbb{K}\left(\frac{u+\hat{U}_i}{h}\right) \mathbb{K}\left(\frac{v-2+\hat{V}_i}{h}\right) \\
+ & \mathbb{K}\left(\frac{u-2+\hat{U}_i}{h}\right) \mathbb{K}\left(\frac{v-\hat{V}_i}{h}\right) + \mathbb{K}\left(\frac{u-2+\hat{U}_i}{h}\right) \mathbb{K}\left(\frac{v+\hat{V}_i}{h}\right) \\
+ & \mathbb{K}\left(\frac{u-2+\hat{U}_i}{h}\right) \mathbb{K}\left(\frac{v-2+\hat{V}_i}{h}\right) \Bigg]
\end{aligned}$$

where $\mathbb{K}$ is a primitive for $K : R \to R, \int K = 1$ and h is a bandwidth sequence such that $h_N \to 0$ when $N \to \infty$.