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Household consumption inequality in Argentina: A regression-based decomposition analysis

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Abstract

In this paper, we examine and analyze household consumption expenditure inequality in Argentina using a regression-based approach. Using data from the National Household Expenditure Survey for the period 2017/2018, we perform a Fields decomposition in order to analyze and quantify the main determinants of inequality in consumption. We estimate a regression model with the logarithm of the monthly household consumption expenditures per capita. The proposed model explains 55.94% of the variability in the dependent variable. As independent variables, we used household size, home environment learning which summarizes the years of education of all adult household members, geographical region, wealth related factors, personal traits of the household head such as work status, age and sex. All variables were significant at 1%, except sex which was significant at 10%. We found that household size and education are the main determinants of consumption inequality, contributing roughly to 38% and 25% respectively. Geographical region and wealth-related variables are also important but to a lesser extent. Finally, work status, age and sex have a negligible contribution to inequality. These results are important and should be taken into account for designing public policies aimed at reducing inequality and increasing well-being.

Keywords consumption expenditure inequality · regression-based decomposition · Household size · Education · Argentina

JEL classification codes D63 Equity, Justice, Inequality, and Other Normative Criteria and Measurement – C21 Cross-Sectional Models, Spatial Models, Treatment Effect

Models, Quantile Regressions – E21 Consumption, Saving, Wealth – D31 Personal Income, Wealth, and Their Distributions

Introduction

In this article, we analyze consumption inequality in Argentina. The study of this subject is relevant because it is an important measure of welfare and living standards. Consumption is a measure of realized well-being in a more straightforward way than income; besides, it is often smoother and less volatile (Trang et al, 2026). Persistent high inequality may threaten social and political stability, the sustainability of democracies and the social security system (Rani & Furrer, 2016; Pieters, 2010; Kapstein & Converse, 2008; Villanthenkodath et al., 2024), therefore public policies should be focused on reducing inequality and increasing well-being. In order to achieve their objectives, they must understand its drivers and take into account its causes and related factors.

According to Official Reports from The National Institute of Statistics and Censuses (INDEC) and academic research (Alvaredo et al., 2025; Rani & Furrer, 2016), income inequality measured in Argentina has fluctuated along its economic history with periods of rise and decline, being rather stable in the last years. Consumption inequality, which is closely related to, on the other hand, has not been studied, at least to our best knowledge. One aspect to remark on is that household income is measured continuously through household surveys, whereas consumption expenditure is measured irregularly (Attanasio and Pistaferri, 2016). Nevertheless, consumption is more closely linked to quality of life and need fulfillment.

Since consumption inequality has several implications, its study requires a rigorous examination of its underlying determinants. For this purpose, this study investigates the socioeconomic and demographic drivers of household consumption expenditures employing a regression-based decomposition approach to assess the quantitative contribution of socioeconomic and demographic factors to overall inequality.

Understanding consumption inequality in households is useful and important for designing better public policies such as tax reforms, welfare programs, family transfers, and labor laws that improve welfare and well-being.

The study of household consumption inequality is a complex and multicausal phenomenon (Ayyash & Sek, 2020). From a theoretical perspective as well as from empirical results, several demographic and economic factors are determinants for household consumption. Economies of scale are very relevant when analyzing household welfare. According to economic theory, several items of household consumption have characteristics of public goods, thus if two households have the same income or expenditure per capita, the larger one is expected to have a better living standard since public goods can be utilized by all members, but requires only one purchase (Deaton and Paxson, 1998; Kufenko, et al., 2018; Ravaillon, 2016; Echeverría & Molina, 2023).

The goal of this article is to determine and quantify the relative importance of factors that contribute to household consumption inequality in Argentina using Fields (2003) decomposition method, which as far as we know has not been applied to Argentina. The

results from the study allow a better understanding of the drivers of inequality and may help to design better public policies that aim to improve well-being. To achieve the proposed objective, the article is organized as follows. Firstly, a brief summary of decomposition methods is presented alongside a review of relevant studies conducted in other countries. Secondly, the data used, that is the National Household Expenditure Survey is detailed explained: its recollection methods, some limitations the variables used, and some descriptive statistics. Thirdly, the empirical methodology strategy is presented. Next, the results are shown and discussed, and comparison with other studies and countries is made. Moreover, public policies implications are considered. Finally, conclusions of the study are summarized.

Literature review on inequality decomposition methods

Decomposition methods and analysis have a long tradition in economics and have proved to be remarkable tools. Numerous questions can usually be answered through decomposition methods, both in macroeconomics and microeconomics (Fortin et al., 2011). For example, at the macro-level, sources of economics growth are decomposed into those attributable to labor, capital and technological progress (Oosterhaven, 2024) or GDP fluctuations can be decomposed into disturbances that have a permanent effect on output and those that do not (Blanchard and Quah, 1989; Gulli, 2005). At the micro-level, several decompositions for income, consumption or wealth have been proposed and applied (Fields, 2003; Morduch & Sicular, 2002; Shorrocks, 1982, 1984; Vesa-Matti & Schief, 2026).

We will focus on microeconomic techniques of inequality decomposition measures which have long been applied. They are usually classified into classical methods and regression-based methods. Traditional methods decompose income by sources or factor components (Pyatt et al, 1980; Shorrocks, 1982), that is, functional distribution of income by sources such as wages, interest, rents or profits; or by partitioning population into subgroups (age or education) that are categorical and mutually exclusive in order to split total inequality into within and between groups (Cowell & Jenkins, 1995; Gunatilaka & Chotikapanich, 2009; Shorrocks, 1984).

These methods, while useful, have some limitations. First of all, they are mostly descriptive, and do not measure contributions of characteristics to inequality (Manna & Regoli, 2012). Besides, they are also criticized because there might be endogeneity issues or explanatory variables cannot be continuous (Morduch & Sicular, 2002). This is problematic in variables such as age. Finally, as Morduch & Sicular (2002) point out, working with multiple factors is cumbersome since the number of groups increases rapidly as more categories are considered for each factor. This may result in the number of observations in some groups being too small, making estimates of population moments unreliable. Regression-based methods address some of these drawbacks since with them it is possible to use continuous variables and control for endogeneity. Additionally, they enable researchers to deal with factors of different kind such as economic, social, demographic and regional (Gunatilaka & Chotikapanich, 2009)

Regression-based approaches are quantitative methods that were developed originally by Blinder (1973) and Oaxaca (1973), but initially they did not gather much attention until

recently (Ayyash & Sek, 2020; Manna & Regoli, 2012; Gunatilaka & Chotikapanich, 2009; Tripathi, 2018). Several authors developed further and applied this methodology (Bigotta et al., 2015; Fields, 2003; Morduch and Sicular, 2002; Wan 2002, 2004; Yun, 2006). Chantreuil et al. (2019) and Fourrey (2023) uses a decomposition that relies on the Shapley function. It is a unified mathematical method to break down inequality indices into distinct parts: the sum of pure marginal contributions of income sources and the sum of pairwise interactions. This decomposition is based on game theory, treating each factor as a "player" generating total inequality, and it is valid for both decomposition by components and subgroups.

An interesting method of decomposition is due to Fields (Fields, 2023; Morduch & Sicular, 2002). This regression-based technique allows researchers to break down consumption or income inequality into the exact percentage contributions of each individual explanatory variable or factor, and it can be used with different inequality measures. It needs first to fit a linear regression model where the dependent variable is the logarithm of consumption or income, which is explained by a set of covariates and a residual term. With the estimated regression coefficients, the method assigns a share of the total inequality of the variance of the dependent variable to each explanatory variable Fields (2003).

Another advantage of decomposition methods is that they allow not only the detection of inequality but also the quantification of the determinants of inequality (Wan, 2002). When designing public policies, it is important not only to know the impact of a policy public instrument on a policy objective, but also to know the extent of its contribution to the other variables in order to avoid public policies that weight wrongly (Furrey, 2023). That is, if education contributes in a large proportion to inequality while housing prices do not (Miles, 1997), a public policy should emphasize the first one.

In this article, we will work with the decomposition method proposed by Fields (2003). As this method requires as a starting point a linear regression, it is important to model the data-generating process. Because the dependent variable is consumption, which is intrinsically linked to income, several theoretical frameworks have tried to explain its determinants and its variability.

Traditional theories such as the life-cycle hypothesis and permanent income hypothesis “constitute the workhorse theory of how people make their consumption decisions” (Attanasio y Pistaferri, 2016, p. 9). Accordingly, consumption can be considered as a fraction of permanent income. Since consumption yields utility or well-being, households prefer a smoother path for it and consume a fraction of their permanent income rather than current income, which is composed by both permanent and transitory income. Furthermore, “income streams exhibit transitory fluctuations” (Gunatilaka & Chotikapanich, 2009, p. 885). Consumption smoothing may be achieved through savings, borrowing and insurance, among others, depending on the institutional setting and the individual situation. If capital markets are not developed or household has restrictions to borrow money, then it is likely that consumption is more dependent on current income rather than permanent income (Deaton, 1991; Miles, 1997). Permanent income is related to long-term determinants of income, such as human capital and skills,

while temporary income may depend on short-term factors such job changes or fertility (Attanasio y Pistaferri, 2016).

Other factors that might influence consumption inequality are age and sex of the household head. Permanent-income hypothesis and life-cycle theory suggests that consumption is smoothed across lifetime, thus consumption fluctuations are expected to be smaller than income fluctuations under these frameworks (Krueger & Perri, 2006), and the adjustment is made by savings. Theoretically, because consumption tends to be stable, whereas income has an inverted U-shape with age, correlation between per capita consumption and age should expected to be weak.

Family structure can in principle act as an amplifier or mitigator of economic inequality not only because family members can provide insurance to each other but also because overtime much of the human capital investments for the next generation are made within families (Santos & Tertilt, 2024). Since the influence of household size in the study of consumption patterns is well documented in the literature (Bick & Choi, 2013), it is expected to be an important factor in consumption inequality. These variables might be inversely related because of economies of scale, family public goods and bulk purchasing discounts. That is, as more people live together, they can share costs and resources that lowers costs per person. If households consume both public and private goods, the former can be shared among family members and generate economies of scale (Barten, 1964; Casado et al., 2025).

Several empirical studies have used the regression-based approach to decompose sources of inequality based on these theories to a build up a function to explain the dependent variable, albeit it is worth mentioning that it is not an easy task to find an appropriate function for consumption that is consistent with economic theory as it is pointed out by Miles (1997). Research may focus on income, either by source or by traits, as well as by consumption characteristics. (Bigotta et al., 2015; Fields, 2003; Brewer & Wren-Lews, 2016; Nwosu et al, 2018; Rani & Furrer, 2016; Tripathi, 2018).

Fields (2003) himself performs a decomposition analysis for the United States. He founds that the most important factor is education, experience and sex, while others such as region, race and industry has almost no contribution. He remarks that “these differences in relative importance could not have been seen from standard regression output alone” (Fields, 2003, p. 22). That is, while all variables are statistically significant, their contribution may be very different.

Brewer & Wren-Lews (2016) for the UK conclude that income inequality increased between 1978 and 1991 and stayed stable onwards. Furthermore, as regards investment and pension income inequality has diminished from 1991 as well as the gap between employed and unemployed. Even more, elderly households and households with little children have seen their income converge. Bigotta et al. (2015) investigated the main causes of inequality in India and found that the two main determinants influencing income disparity both, in rural and urban areas are, education and household size, followed by job status and geographical region.

Rani & Furrer (2016) analyze income inequality in 13 countries of the G20, which has been rising in recent years. In order to design effective public policies, it is important to

understand the drivers of inequality. Their results show that labor income is the primary factor that explains inequality, while transfers and benefits reduce it. Moreover, the main factors that contribute to labor income inequality are employment status and education, while age, sex, and industry sector play a role in some countries. Using a regression decomposition approach with Shappley Value framework, Wicaksono et al. (2017) found that the main sources of income inequality are education, wealth and employment sector for Indonesia. Thus, they recommend that policy design should try to reduce gaps in education and financial access in order to decrease inequality.

Ayyash & Sek (2020) analyze consumption expenditure inequality in Malaysia using Fields decomposition. Their regression model explains about 55% of the variability in the logarithm of monthly consumption per capita. Their results show that household size, education of household head a regional heterogeneity are the main factors that explain inequality. For the Italian case, Mana and Regoli (2012) analyze income inequality using both Fields and Shapley methods of decomposition. Their results indicate that capital both human as non-human and the gender factor are the most important determinants while region and work status have a minor impact. In the Vietnam case, Tran et al. (2024) also working with a household survey and practicing a Fields decomposition found that the dominant determinants are the human capital (including labor, age, education and ethnicity), and physical capital (means of transport owned by the household and information access by the family) remarking that the education factor have played a significant role to reduce disparities.

Overall, from the literature review across multiple countries and relative recent periods studies that used a similar methodology to the one we apply here, we conclude that the regression models have an explained variance of the dependent variable between 30% and 60% and household size and education as well as regional heterogeneity tend to be major factors that contribute to consumption or income inequality. This is expected from a theoretical point of view and as we will show in the results section, similar findings are also present in the case of Argentina.

Data

The National Household Expenditure Survey (Spanish acronym: ENGHo) is the source of household expenditure data in Argentina. This is a large-scale survey, and it was conducted by the National Institute of Statistics and Census (INDEC) between November 2017 and November 2018 (Instituto Nacional de Estadística y Censos [INDEC], 2019). It is a survey that is nationally representative of the urban population, and it is cross-sectional. This comprehensive dataset provides critical insights into household economics, particularly spending. Results from the survey are publicly available, and microdata can also be downloaded as text files.

The microdata spans several database files, including specific datasets for household information, and another one for each household member, among others. Variables collected include dwelling information, as well as demographic and economic traits at both the household and individual members. It also provides a detailed record of individual expenditures, as well as common household expenses such as utilities.

Consumption includes twelve large items such as food, beverages, clothing, utilities, and each one is disaggregated until a specific article is obtained. Total household consumption is obtained by adding all items for all household members. Data is collected by recalling, with different time frameworks depending on the kind of goods or services. For example, daily expenditures of each member include a 7-day period, while utilities are usually on a monthly basis. For items that are less frequently bought or sold, such as cars, the survey asks if there was a transaction in longer periods, up to a year.

Consumption expenditure is also expressed on a monthly, per capita basis using an adult equivalent scale computed by INDEC. The use of an adult equivalent is necessary to adjust for children or elderly, since they typically consume less than adults meaning policy must weigh household members differently. In fact, market prices sometimes take this heterogeneity into account, for instance, theatre or theme parks tickets are less expensive for the children or retired, or public transportation is sometimes free.

The data survey is divided in four operational quarters, and it can be disaggregated down to the first-level administrative division (provinces). There are 21,547 households and 68,725 people in the whole dataset. Because inflation was moderate during the period of the survey, we decided to use only the final operational quarter to mitigate its effect on consumption expenditure. However, robustness checks using the full dataset yielded no significant changes in the results. The final quarter contains 5,481 households. We worked at the household level, and personal traits are those of the household head. After removing a few records with missing values, the final sample consists of 5,453 households.

The survey data measures mostly household expenditures, which is closely related to consumption, but in a strict sense they are not the same (Attanasio and Pistaferri, 2016; Eika et al., 2020). Consumption refers to the actual use or satisfaction derived of goods and services, while expenditure is the monetary transaction of buying a good or service. Therefore, some goods may be acquired in a different period than it is consumed. Also, durable goods are bought in a moment in time but provide services gradually across their lifespan. In the case of other items, such as food, consumption and expenditure are almost identical. Nonmarket production and in-kind received goods have zero expenditure but consumption is positive. Imputed income or expenditures of some of such items are present in the survey. For example, in-kind received goods are considered as income and they are valued at market prices.

One limitation of this is that evaluating inequality by looking at household expenditure instead of consumption may lead to biases. For example, a self-sufficient rural family will look poorer than it really is because its market transactions are near zero. Nevertheless, in our database this is a minor issue, since the dataset includes only urban households, where transactions are mostly on the market. Also, we have attempted to mitigate this by including geographical regions in the regression model. Similarly, dwelling ownership is an important variable for households, nevertheless, rent is not imputed for those households that do own their homes in our database, while it is considered as an effective expenditure for those households that do not own it. For this reason, we have excluded home ownership as a regressor. In richer urban regions it is found in Argentina and other countries that there are less homeowners (Basso & Gulli, 2024). If home

ownership were included as an independent variable, it would be found that households that rent would present a higher expenditure and therefore greater well-being, when in fact, the opposite is true, since at least in Argentina, households that own their home are better off. However, the use of household consumer expenditure as a proxy of an inequality method have been broadly used in the literature especially in the micro level studies (Ayyash and Sek, 2020; Bigotta, et al. 2015; Tripathi, 2018).

Table 1 shows the variables that were used and some descriptive statistics. Household size, that is the number of members composing the home is on average 3.2307 members per household, with a standard deviation of 1.8555. The average age of household head is 50.7141 years with a standard deviation of 16.1737. As regards household head sex, the proportion is quite similar, since 55.38 % are male and 44.62 % female. Employment or occupational status is also referred to the head of household, where around two-thirds are employed, that is, they did at least one hour of work activities either independently or self-employed. The unemployed are those who are actively looking for a job, represent 3.69 %, and those inactive, i.e., retired people, are 31.67%.

Home learning environment or educational climate of the household is a measure computed directly by INDEC which refers to average years of schooling achieved by adults (18 years old or more) of the whole household. While some studies choose the head level of education, our methodological strategy was to use this variable because it includes all house members. Tran et al. (2024) use a similar approach. It has five categories from very low to very high. Low categories are usually households with elementary school or incomplete high school, intermediate categories have finished high school with perhaps some years of college incomplete, and the highest categories involve finishing university or post-graduate degrees.

Wealth variables may be related to consumption (Manna & Regoli, 2012); nevertheless, the survey does not include a wealth measure. However, it has detailed information about household equipment, such as microware, oven, washing machine, air-conditioning, car ownership, etc. Since these variables are indicative of wealth, they can be used to measure wealth (Filmer & Pritchett, 2001; Montgomery, et al, 2020), and we have included them. Particularly, we focused on car ownership and whether the dwelling has air conditioning. In the first one, 54.41% of households do not own a car, 39.98 % own one car and the rest own two or more cars. As regards air-conditioning, the proportion is very symmetric, 50.91 % of households do have it.

Finally, households were identified as to their regional location. The metropolitan region includes Buenos Aires city, the capital of the country, and its metropolitan area that spans across the neighboring of the Buenos Aires Province. The Pampena region is a very important one, where most major cities are located and have a diversified economy; it is geographically in the center of the country. Patagonia is on the south, and it is sparsely populated with specific economic activities such tourism or natural resource extraction. Cuyo is on the center-west of the country. North regions are usually the least developed in the country, especially Northeast. Because regions have very different socio-economic characteristics, and different productive economies, heterogeneity among regions, it is expected that consumption patterns vary across them.

Table 1 Descriptive statistics

Continuous Variables	Mean (Standard deviation)
Logarithm of monthly household consumption	8.8144 (0.8529)
Household size	3.2307 (1.8555)
Age of household head	50.7141 (16.1737)

Dichotomous Variables	Proportion
Head of household sex	
Male	55.38 %
Female	44.62 %
Employment status	
Employed	64.64 %
Unemployed	3.69 %
Inactive	31.67 %
Home learning environment	
Very low	9.06 %
Low	36.86 %
Intermediate	32.39 %
High	13.30 %
Very high	8.40 %
Car ownership	
No car	54.41%
One car	39.98 %
Two or more cars	5.61%

Dwelling has air conditioning	
No	50.91 %
Yes	49.09 %
Geographical region	
Metropolitan	18.19 %
Pampas	23.69 %
Northwest	22.63 %
Northeast	13.22 %
Cuyo	9.11 %
Patagonia	13.15 %

Notes: Authors' calculations based on the National Household Expenditure Survey, Argentina, 2017/2018.

Empirical modelling strategy

First of all, a log-linear regression model is estimated that we deem appropriate not only because the coefficients can be interpreted as semi-elasticities but also because it trims down the influence of skewness on the distribution of expenditures, which tends to be heavily left-skewed.

Therefore, we will consider that household consumption expenditure per capita can be modeled as a function of economic and demographic variables following a log-linear specification:

$$\ln c_i = \alpha + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots \beta_k x_{k,i} + \epsilon_i \qquad (1)$$

where the dependent variable is c_i, that is, the monthly consumption expenditure per capita for household i, and the independent variables are $x_{1,i}, x_{2,i}, \cdots, x_{k,i}$. Those include household size, age of household head as numerical variables; and several dichotomous variables: sex and work status of the household head, home learning environment, car ownership, whether dwelling has air-conditioning and geographical region. Details and descriptive statistics of these variables were shown in table 1 in the data section.

The parameters are the intercept α, and the coefficients for each regressor, that is $\beta_1, \beta_2, \cdots, \beta_k$. Finally, ϵ_i is the error term. The independent variables can be of various types or even proxies (Fields, 2003; Wan, 2004), specifically we have used continuous and dummy variables. This is an advantage of this decomposition, because it is more flexible in the variables that can be used. Parameter estimation is carried out by ordinary least squares (OLS).

Also, it is important to note that regression-based decomposition methods usually distinguish between variables and factors (Fields, 2003) or variable and attributes (Furrey, 2023). Factors or attributes refer to the general category, while variables can be subcategories, or one variable may constitute a factor. Therefore, if the regression includes education as a factor or attribute, it may have several variables, for instance education and education squared; similarly, several dummy variables for labor condition (employed, unemployed, retired) can be an attribute or factor that would establish the work status. That is a variable can be an attribute or factor, or a set of independent variables can be represent one attribute or factor (Fields, 2023, Furrey, 2023).

Applying covariance to both sides of equation (1) and taking into account that the covariance of a variable with itself is the variance, the decomposition developed by Fields (2003) is obtained. The relative factor inequality weight that is assignable to each explanatory variable is expressed as follows:

$$s_j(\ln c) = \frac{\beta_j \cdot \operatorname{cov}\left(x_j;\, \ln c\right)}{\sigma^2(\ln c)} \tag{2}$$

where $s_j(\ln c)$ is the mentioned weight, β_j is the coefficient of the independent variable x_j, $\operatorname{cov}\left(x_j;\, \ln y\right)$ is the covariance between x_j and the dependent variable (logarithm of consumption), and $\sigma^2(\ln c)$ is the variance of the dependent variable. The weights are usually positive but can be negative if the partial correlation coefficient of the multiple regression has the opposite sign of the simple correlation coefficient (Bigotta et al., 2015).

When all inequality weights are summed, the result is the R-squared, that is, the coefficient of determination of the regression (Ayyash & Sek, 2020; Fields, 2003; Manna & Regoli, 2012):

$$\sum_{j=1}^{k} s_j(\ln c) = \sum_{j=1}^{k} \frac{\beta_j \cdot \operatorname{cov}\left(x_j;\, \ln c\right)}{\sigma^2(\ln c)} = \frac{\sigma^2(\ln \hat{c})}{\sigma^2(\ln c)} = R^2(\ln c) \tag{3}$$

where $\hat{c}$ are the values predicted by the estimated model. Therefore, the method provides an exact decomposition of the log-variance (Fields, 2003), that is, it is 100% provided that the residual term is included.

If we exclude the residual term, each inequality weight factor can be normalized by dividing it by the coefficient of determination, in which case the sum will equal one, that is:

$$p_j(\ln c) = \frac{s_j(\ln c)}{R^2(\ln c)} \tag{4}$$

Where $p_j(\ln c)$ is the normalized weight, such that

$$\sum_{j=1}^{k} p_j(\ln c) = 1 \quad (5)$$

One interesting feature of the decomposition is that it can be applied to other measures, such as the Gini coefficient, under mild conditions; that is, the decomposition remains valid for other inequality metrics, not just the log-variance (Fields, 2003). However, it cannot be applied to any inequality measure, for instance, Bigotta et al. (2015) shows that the decomposition cannot be applied to Atkinson index, and they develop an extension of this methodology for such case.

Results and discussion

Here we present the key findings regarding consumption inequality decomposition by characteristics following the regression-based approach in Argentina for the year 2018. First, we show the results of the consumption function estimation. Then, we exhibit the regression-based decomposition of consumption inequality and the relative contribution of each factor. We also discuss the results, compare them with other studies, and analyze the implications for public policies.

The results of the estimated linear model for the logarithm of consumption expenditure per capita from equation (1) are shown in Table 2. All independent variables have the expected sign and are significant at 1% except sex of the head of household, which only is significant at 10%.

As regards the continuous regressors, we have included household size and age of household head. The estimated coefficients are -0.19442 and 0.00242 respectively. The first one indicates that if there is an additional member in the house, for instance, a newborn, consumption expenditure per capita decreases by approximately 19.44%. Family size and structure is also relevant when analyzing at the household level, and it is well known to have an impact on consumption per capita inequality (Ayyash & Sek, 2020; Bick & Choi, 2013; Bigotta et al., 2015; Deaton & Paxson, 1998; Trang et al., 2026; Xue et al, 2026; Wan, 2004). This relationship operates through two main channels: income sharing and economies of scale. When household size increases, resources may also increase, but to a lesser proportion than the increase in the number of members. Thus, total available resources and resultant consumption per capita are reduced. Larger families might gain advantages from common household resources and expenditures, such as housing public goods and utilities. Therefore, per capita expenditure does not necessarily increase in the same proportion as the number of members (Trang et al., 2026), resulting in a diminishing per capita consumption.

The coefficient of age shows that if there is an increase in one year of the household head, consumption expenditure per capita increases by roughly 0.242%. While this coefficient is statistically significant, its value is very low, showing a minor impact on consumption. This result is expected, and may be due to the fact that, while income may increase with age because more experience and human capital is accumulated, consumption, on the other hand, is smoothed across the life cycle.

Regarding categorical regressors, sex has the expected sign, but it is only significant at 10%. Its value is -0.02803, showing that a household with female head has an approximate 2.8% less consumption per capita. Work status coefficients are -0.32159 and -0.07609 for the unemployed and inactive respectively, being employed the base category. Thus, households whose head is unemployed spend approximately 32.16% less, while those with retired household heads spend nearly 7.61% less than those with an employed household head. This result is expected and found in other studies (Bigotta et al., 2015; Manna & Regoli, 2012). This is reasonable since having an employed household head implies higher resources available for consumption.

Home learning environment is also statistically significant, and it has the expected sign. This variable is an average of the years of schooling of all housing members older than 18 years, and it has five categories from very low to very high, the base being very low. Coefficients are positive and monotonically increasing, indicating that a better home learning environment is associated with more household consumption per capita. On average, consumption of households with low home learning environment has an approximate 14.93% higher consumption per capita than those with a low value. Similarly, coefficients for intermediate, high and very high household learning environment are 0.38474; 0.65375; 0.83410. Thus, for instance, if we compare the extreme categories, a household with very high learning environment has an approximate 83.41% higher consumption per capita than the reference category. Thus, consumption is greatly affected by returns on education, and similar results have been found in other studies (Ayyash & Sek, 2020; Bigotta et al., 2015; Furrey 2023; Miles, 1997; Morduch & Sicular, 2002).

Number of cars owned by the household and whether the dwelling has air-conditioning were chosen as proxy variables to measure wealth, since the survey does not have a specific variable for the latter. Wealth is an indicator of non-human capital that usually generates an income flow from rent and interests, and it should be an important determinant of consumption (Manna & Regoli, 2012). For numbers of cars owned, the base category is zero. Results show that if a household owns one car, it has an approximately 31.78% higher consumption per capita, while if it owns two or more cars, it has 62.65% higher consumption per capita, both in relation to having no cars at all. Regarding air-conditioning, on average consumption per capita is 15.90% higher on households that have this appliance. Finally, results show that consumption per capita varies with geographical regions, particularly all of them have a lower consumption per capita than the metropolitan area of Buenos Aires. This area is the largest populated of the country, and it also has a high GDP, so this is not surprising. Furthermore, heterogeneity in consumption or income per capita across regions is also found in other countries (Ayyash & Sek, 2020; Bigotta et al, 2015; Manna & Regoli, 2012).

The adjusted R-squared coefficient is 0.5534, which shows a very good overall fit, since nearly 55% of the variation of the logarithm of monthly consumption expenditure per capita is explained by the model. Particularly in comparison with other studies on the same topic and this methodology we obtain a higher R-squared than Brewer & Wren-Lewis (2016), Fields (2003), Gunatilaka & Chotikapanich (2009), Manna & Regoli (2012), and Tran (2024), and similar to Ayyash & Sek (2020).

Table 2 Regression results.

Variable	Estimate	Standard Error
Intercept	9.09025	0.05038
Household size	-0.19442	0.00454
Age of head of household	0.00242	0.00060
Head of household sex (base category: male)	-0.02803	0.01640
Occupational status (base category: employed)		
Unemployed	-0.32159	0.04165
Inactive	-0.07609	0.02109
Household learning environment (base category: very low)		
Low	0.14932	0.02940
Intermediate	0.38474	0.03119
High	0.65375	0.03613
Very high	0.83410	0.04067
Number of cars owned by the household (base category: none)		
One	0.31777	0.01788
Two or more	0.62645	0.03655
Dwelling has air conditioning (base category: no)	0.15897	0.01773
Geographical region (base category: metropolitan)		
Pampas	-0.22773	0.02445
Northwest	-0.43777	0.02487
Northeast	-0.73291	0.02873
Cuyo	-0.35730	0.03160

Patagonia	-0.14843	0.02976
R-squared	0.5548	
Adjusted R-squared	0.5534	

Notes: consumption function estimation. Dependent variable: logarithm of monthly household consumption expenditure per capita. All independent variables are significant at 1%, except sex which is significant at 10%. Authors' estimations based on the National Household Expenditure Survey, Argentina, 2017/2018.

The results for the inequality decomposition in consumption are shown in Table 3 and Figure 1. Table 3 presents the relative factor inequality weights including the residual term, and as a percentage of the R-squared, that is, excluding the residual term, computed using equations (2) and (4). Figure 1 shows the normalized weights in a donut-type graph for visual appreciation. The explained variability of the log-variance accounts for 55.49% while the residual term accounts for 44.51%.

The largest portion of this pie corresponds to the size of the household representing 38.32% of the consumption per person of each household, followed by the educational environment of the family, 24.59%. The geographical region explains half of what explains the size of the household; that is, 17.86% of said expenditure. In fourth and fifth place of relevance when explaining the variability in consumption are the possession of a car and air conditioning, variables related to the wealth of the household as mentioned (13.74% and 3.22% respectively). Finally, 1.84% is explained by occupational status and variables such as sex and age practically do not explain a substantial part of consumption inequality.

The results are similar to those from other studies, and in general, household size and education tend to be major factors contributing to inequality (Ayyash & Sek, 2020; Bigotta et al, 2025; Brewer & Wren-Lewis, 2016; Gunatilaka & Chotikapanich, 2009; Manna & Regoli, 2012; Trang et al., 2026; Xue et al, 2026). For instance, if we focus on studies that specifically study consumption inequality, Ayyash & Sek (2020) finds that in Malaysia the dominants factors are household size, education and state with shares of 19.49%, 19.11% and 8.42% respectively. Gunatilaka & Chotikapanich (2009) shows that major contributors to consumption inequality in Sri Lanka are infrastructure (which is a proxy to household wealth) with shares between 12.93% and 25.6%; and education with weights between 10.82% and 15.14%. Bigotta et al. (2015) report for Indian urban population that household size contributes between 14.3% and 21.3% to consumption inequality depending on the year analyzed, while education contributes between 21.1% and 28%. These factors are the main contributors to inequality for both rural and urban households. Nevertheless, they are higher in urban areas. Employment status is much less important, especially in urban areas. While consumption and income are intrinsically linked, they are not the same concept, and when analyzing inequality, a difference seems to appear as to which factors are major contributors. For instance, work status seems to have a much less impact on inequality when analyzing consumption than income.

As regards Argentina, we do not know of previous studies that have analyzed consumption inequality with this method, however, Rani & Furrer (2016) do make a labor income decomposition using Fields approach for selected G20 countries, and their study includes Argentina. They use The Permanent Household Survey, which collects data on income on a permanent basis, but does not include expenditure data. Also, this survey covers 31 large cities, while the survey we used covers all urban areas. Nevertheless, both surveys share aspects, for instance labor and income, dwelling information; and demographic information is gathered in a similar way. They include as covariates age, sex, marital status, household size, education, employment status, number of jobs, industry and region. Comparing their results to ours, our R-squared is higher, and education is an important factor; however, employment status is the major contribution to income, which should not be surprising since the dependent variable is labor income. More surprisingly, household size has a minor contribution to labor income inequality, while we have shown that for consumption expenditure, it is the primary factor that contributes to inequality. Other variables such as age and sex have very low contribution to both consumption expenditure and labor income inequality.

Table 3 Fields decomposition results.

Variable	Relative factor inequality weight (%)	Relative factor inequality weight as % of R-squared
Household size	21.26	38.32
Age of head of household	0.17	0.31
Head of household sex	0.07	0.12
Occupational status	1.02	1.84
Household learning environment	13.64	24.59
Number of cars owned by the household	7.63	13.74
Dwelling has air conditioning	1.79	3.22
Geographical region	9.91	17.86
Total	55.49	100.00

Notes: Authors' estimations based on the National Household Expenditure Survey, Argentina, 2017/2018.

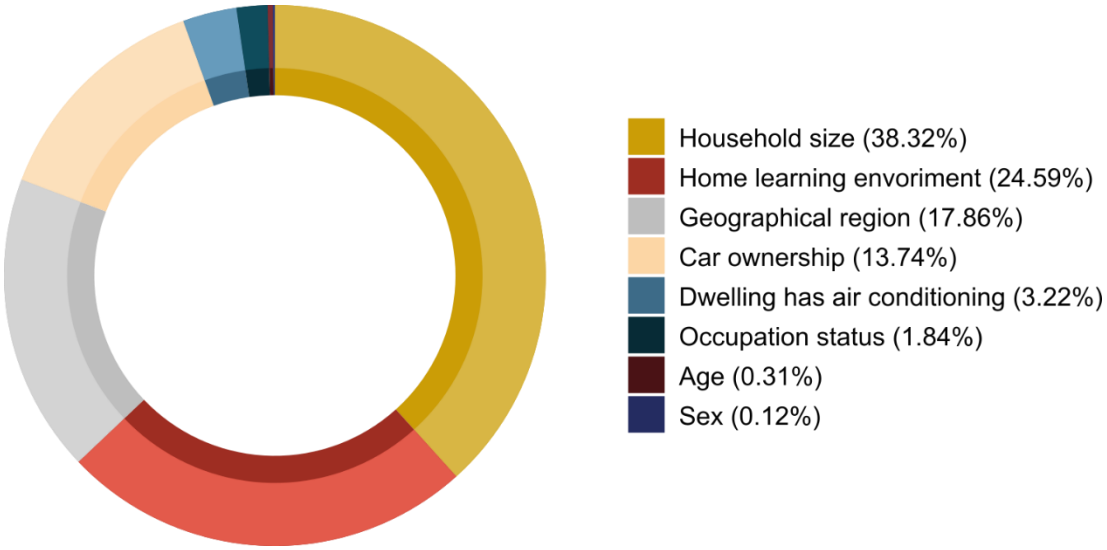


Fig. 1 Fields decomposition: Relative factor inequality weight as % of R-squared.

Finally, public policies aimed at increasing household welfare could take into account these factors in order to achieve their goals. The inverse relationship between household size and consumption impacts how government measures poverty, distribute social welfare and calculate progressive tax systems. Because large households share expenses, standard per capita metrics often hide their true economic well-being, leading to public policy misallocation. While this particular survey considers equivalent-adult scales to make comparison, many metrics and public policies consider only traditional per capita metrics, such as GDP per capita, which may lead to wrong conclusions, implying that there might be more (or less) inequality gap between comparisons.

Regarding distribution of social welfare, the goal is to avoid penalizing families in worse conditions. However, the opposite may occur if household size is not taken into account. Fixed cuts off or thresholds can disqualify large families who still struggle with fixed costs. For example, in Argentina, there exists energy assistance programs for household electric power and natural gas subsidies. In order to quality a household must have a total income less than a specified amount. This amount is calculated based on only one type of household size, therefore, smaller households may qualify even though their income is rather high, while larger households may be struggling but unable to quality due to its size only.

Similarly, utilities prices are calculated based on several parameters, however, household size is not taken into account. In this sense, flat fees favor larger households, while it hurts smaller households. If fees are tier, with larger consumption having a larger fee, since more consumption is a well-being indicator, larger poorer households may end up paying more because there are more members, and the policy is misaligned. Electric and gas bills, which are regulated in Argentina, are usually computed with a fixed cost and increasing tiers fees based on consumption. Thus, larger households may end up paying larger prices even though they may not have a better quality of life.

Finally, tax policy sometimes fails to account for household size and can inadvertently place a heavier relative tax burden on larger families who, despite lower per capita consumption levels, have less disposable income left for savings. Tax credits (such as child tax credits) help offset the lower per-capita consumption capacity induced by dependents. At the moment of designing tax systems, lowering consumption taxes such VAT would seem a good option. Reduction of VAT on bulk household staples seems a good policy since it benefits larger households, this policy is currently applied in Argentina at the national level. Nevertheless, there are provincial indirect taxes on transactions, which do not necessarily comply with this. Also, since education plays a significant role in explaining consumption inequality, enhancing education policies might lead to better living standards. In Argentina, at the National level, education is exempt from indirect taxes, but there are taxes at provincial and municipal levels.

Conclusions

The study of consumption inequality is critical both from an academic point of view and for its public policy implications as regards well-being and welfare. Let's remember that the main aim of this paper was to analyze the main determinants of consumption and quantify the relative contribution of each factor to consumption inequality in Argentina in 2018. For this purpose, microdata at the household and individual level from the Argentinean Household Expenditure Survey was used, complemented by a brief review of consumption theories and decomposition methods.

In order to examine the drivers of consumption inequality, we applied Fields decomposition, which is a regression-based approach. First, a model for the logarithm of consumption per capita was estimated using several explanatory variables: household size, home environment learning, geographical region. Two proxy variables for wealth were included: car ownership and dwelling possession of air-conditioning, along with traits of the household head (occupational status, age and sex).

All variables were statistically significant at the 1% level, with the except of sex, which was significant at 10% level. Household size, sex and occupational status of household head and geographical region showed negative coefficients; while age of household head, home learning environment and the wealth-related variables exhibited positive slopes.

Finally, the key findings show that household size and home learning environment are the primary factors that explain consumption inequality. Geographical region and wealth related variables make intermediate contributions. On the other hand, work status, age, and sex have minor contributions. Our decomposition provides valuable insights that help understand consumption inequality in Argentina and can be used as guidance for designing public policies aimed at improving welfare.

Declarations

Author contributions Both authors contributed equally to this work. Both authors read and approved the final manuscript.

Conflict of interest The authors declare no competing interests.

Data availability We use publicly available data from National Household Expenditure Survey.

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