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Marginal Propensity to Consume and Income and Wealth Distributions in Portugal: A Panel Household Survey Data Analysis

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Abstract

This work project assesses the role of inequality on households' marginal propensities to consume and calculates their effect on short-run aggregate demand growth in Portugal, between 2004 and 2020. Using household survey longitudinal data, this study shows that MPCs are decreasing on income quintiles and have non-linear distributions by wealth quintiles, implying the existence of MPC heterogeneity. Moreover, aggregate consumption growth is estimated and two important results are achieved: targeted and non-targeted transfers under MPC heterogeneity imply a larger aggregate demand multiplier than under a homogenous MPC and a targeted transfer to the top income quintile leads to overall lower growth.

Keywords: Marginal Propensity to Consume, Inequality, Income and Wealth Distributions, Aggregate Consumption Multiplier, Heterogeneity, Panel Data, Household, Survey

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I. Introduction

Under Post-Keynesian Economics theory, which is based on the Principle of Effective Demand, the short-term equilibrium began to be defined as $Y = Aggregate\ Demand\ (AD) = C + I + G + NX$. C denotes private consumption of final goods by households and individuals, I represents planned investment in capital goods, G is government spending on public goods and infrastructure and NX stands for total exports minus total imports. Hence, to stimulate economic growth (i.e., $\Delta Y > 0$), from a fiscal perspective, the government could expand aggregate demand by increasing G or increasing transfers (or apply tax cuts) to households as to increase total household disposable income and subsequently, boost C (assuming a Keynesian Consumption Function, adjusted to an open economy), ceteris paribus. The above-mentioned rationale is therefore the basis for creating the link between exogenous government intervention, consumption, and output growth.

Regarding households' total disposable income, the aforementioned social transfers can either be financed by government deficits (through aggregate private savings, domestic or foreign) or taxes, following the government's budget constraint. However, as social transfers have merely a distributive role, when abstaining from equity reasons, their economic effectiveness stems from the presumption that, at a micro and subsequently a macro-level, households have heterogenous propensities to consume, conditional on their level of income and net worth, age, household-specific preferences (such as risk aversion), their activity status, among other factors. If consumption responses were homogenous among households, then distributional policies would not have any effect on aggregate consumption (Pistaferri and Saporta-Eksten 2012).

Thus, having established the relationship between aggregate consumption expenditure and economic growth and the link between household consumption and aggregate demand, the research questions postulated in this work project are: how do income and wealth distributions affect aggregate consumption and subsequently, output growth in Portugal? How do the marginal propensities to consume differ across different income and wealth groups? Does ownership of wealth (a stock variable) affect households' consumption levels (a flow variable), at a contemporaneous level? This work project attempts to answer all these questions. Section II shows the existent extensive literature and serves as the basis for further analysis on this topic; section III provides data description and analysis and introduces the estimation model; sector IV describes the methodology used and section V presents the results. Lastly, Section VI derives conclusions and limitations of this work project.

II. Literature review

As mentioned in Section I, this work project acknowledges the existence and subsequent role of the heterogeneity of households' marginal propensities to consume (MPC) on aggregate consumption.

Indeed, this heterogeneity has been widely studied and empirically demonstrated in economic literature. For instance, after calculating, for a period of 4 years, the MPC out of a yearly tax refund for 200 individuals, Gelman (2020) dichotomizes the drivers of MPC heterogeneity into household-specific persistent characteristics and temporary circumstances. Concerning the first, Gelman (2020) provides some examples: the household's degree of impatience (measured by the discount factor), its level of risk aversion, present bias, and problems of self-control. In particular, the author suggests that whatever the temporary circumstances are, the average behavior of the MPC and income over time will depend on persistent characteristics (particularly, on the households' degree of impatience). According to this theory, impatient households will tend to have greater marginal propensities to consume (as the present consumption is relatively more valued) and lower cash-on-hand, or analogously, income available to consume contemporaneously (see Appendix I.2 for full definition). Hence, this paper methodologically acknowledges the effect of persistent characteristics on MPC and justifies the inclusion of a term representing unobserved time-invariant household heterogeneity in the specification of the model of this work project.

Regarding temporary circumstances, the author argues that the MPC is either driven by transitory changes in income or by exogenous or/and endogenous changes in liquidity preferences, that is, the household's MPC depends on its consumption and saving choices conditional on these income (flow) changes or depends on whether households prefer to store their accumulated wealth in more liquid or illiquid assets, inevitably changing their level of cash-on-hand. This latter conclusion is also reinforced by Kaplan, Violante and Weidner (2014), where the authors find that hand-to-mouth households, i.e., "consumers who spend all their available resources in every pay period" and a priori would have extremely high MPCs out of income (Kaplan, Violante and Weidner 2014, 78), possess different wealth levels and how this can affect their overall MPC. Specifically, this study recognizes the existence of "wealthy hand-to-mouth households", who own substantial amounts of illiquid assets (such as retirement insurance plans or housing) but possess relatively low liquidity. Given their significant large amount of wealth, in theory, these households could borrow more easily against their illiquid assets and earn extra income as a result, implying a lower MPC compared to the baseline of no borrowing, in the short run. Moreover, households could choose their liquidity portfolio (i.e., through the buying and selling of their assets, they choose their level of cash-on-hand), which would then have an impact on their current available income. Assuming consumption is smoothed when income changes are transitory, households MPCs would decrease as well in this case. Thus, Kaplan, Violante and Weidner (2014) emphasize the role of asset liquidity for households' consumption choices and more importantly, reinforce the need to control for the household's wealth stock when estimating the impact of temporary changes in the household's income flows on consumption. Fisher et al. (2020) also address the heterogeneity in MPCs between different wealth quintiles, by including the main effect of each quintile and its interaction with total disposable income in their specification model. This last study reaches two important conclusions which are expected to be achieved in this work project as well: 1) at a micro-level, on average, lower income households (as well as lower-wealth households) consume a portion of their total disposable income that is relatively larger than their richer counterparts, as the consumption function is presumed to be concave under uncertainty regarding future income (Carroll and Kimball 1996), hence having a greater marginal propensity to consume, ceteris paribus; 2) at a macroeconomic level, under the basis of MPC heterogeneity, targeted intervention by the government (through a lump-sum transfer to poorer income tiers) boosts aggregate consumption and subsequently, stimulates output growth, in the short-run. Jappelli and Pistaferri (2014) also conduct several experiments that reach these two conclusions.

Regarding conclusion 1), another similar perspective is that, under uncertainty, lower-wealth households have stronger precautionary savings motives. I.e., under uncertainty regarding future income, households save more and endogenously delay current consumption (Jappelli and Pistaferri 2014), as they are relatively more liquidity constrained under imperfect financial markets (since their levels of collateral are relatively lower); hence, a unit increase in current income implies that low-wealth households are able to hedge consumption against future income shocks, without having to depress current consumption. Therefore, "the decline in the intensity of the precautionary motive as cash-on-hand rises allows consumption to rise faster than it would in the absence of a precautionary motive" (Carroll 2001, 35), i.e., the marginal propensity to consume out of a transitory change in income is higher for households with a strong precautionary motive (which are, unsurprisingly, lower-income and lower-wealth households). This means that high levels of inequality in income and wealth distribution cause strong MPC heterogeneity and reinforce the effect of strong precautionary savings in the lower tiers of the distribution, which may hamper the boost in aggregate demand and subsequently economic growth (Bivens and Banerjee 2022).

Lastly, literature also justifies the use of wealth variables to avoid the important problem of omitted variable bias and endogeneity. Households with larger income tend to own higher valued assets, such as more expensive housing properties and cars, and larger financial assets (Caceres 2019). Also, as households' level of wealth is generally more static than income, it impacts the lifetime consumption path, under the Permanent Income Hypothesis, as, for example, it can serve as self-insurance and as collateral for household borrowing in case of a negative fall in income in the previous period to smoothen consumption (Fisher et al. 2020). Hence, in this way, feedback effects can be controlled.

In the light of the extensive vast literature on the estimation of households' marginal propensities to consume out of income, conditional on their wealth levels and other factors and subsequently, transposing the micro-level deductions to macroeconomic conclusions, this work project's main objective is to contribute to Portuguese literature on this matter, which is currently scarce. Although the basis of this study relies almost exclusively on papers on the U.S., specific features of the Portuguese economy must be acknowledged and considered when interpreting the results. The wealth composition highly differs between the two countries. In 2022, currency and deposits represented, on average, 48.1% of total financial assets in Portugal while representing merely 13.9% in the U.S.; regarding household debt, in 2021, the latter was 187% of total disposable income in Portugal while 101% in the U.S (OECD 2023). Thus, the conclusions derived from the effect of wealth on MPC out of income in the U.S. may not apply to Portugal.

III. Data and Model

Household-level longitudinal panel data

To find the marginal propensities to consume out of total disposable income of Portuguese households, this study uses the longitudinal component of the ICOR (Inquérito às Condições de Vida e Rendimento), which is curated by Statistics Portugal (Instituto Nacional de Estatística, hereafter INE) and developed under the European Union statistics on income and living conditions framework (the EU-SILC survey). The latter provides individual-level changes over time, which are measured annually over a four-year period and it possesses a successive structure, i.e., panels are constructed from year t to year t+3, year t+1 to year t+4, and so on. In this study, after dropping households that appear only once in the panel (which are redundant in a fixed effects estimation) and split-off households (that is, households that have split in the previous wave, meaning the existence of an additional household), the sample starts with 8760 observations in the first available panel (from 2004 to 2007), ending up with 26,394 observations in the last panel (2017 to 2020), implying a growth in sample size over time. Another important structural characteristic of this panel is that it follows a rotational design, i.e., some part of the sample is rotated from one year to another (implying some households leave and new ones enter) while the other part remains in it, which means that households last between 1 to 4 years in the panel (see Appendix II.2 for detailed panel structure description). This means that each panel is necessarily unbalanced, because the initial sample is only partially retained from one year to the next, leading to rotational group or "time-in sample" bias. However, the latter effects are hard to estimate, as measuring them implies that surveying conditions must be constant across rotating groups, which is rarely true (Baltagi and Song 2003).

The ICOR database includes various characteristics of Portuguese Households, from personal and household yearly (monetary) income variables (Gross and Net) regarding the income reference period (year t-1), demographic characteristics (age, activity status, tenure status, among others) and measures of poverty (such as if the household is able to afford a nutritive meal every second day, or if the household owns basic utilities, such as TV, a telephone, a washing machine, or has a bathroom on its dwelling). Tables 1 and 2 present descriptive statistics on total disposable income- i.e., income after taxes and transfers- adjusted to 2012 base prices, by income quintile (for the first and last panels, 2004-2007 and 2017-2020). Comparing the two panels, one sees that the mean and median household disposable incomes have increased in all income quintiles and dispersion (denoted by the standard deviation) has increased (except in the 5th quintile).

Table 1- Summary Statistics (2004-2007)

Yearly Total Disposable Income (€)						
Income Quintile	Frequency	Mean	SD	Min	Max	Median
1	1752	3524.615	1164.785	31.163	5233.704	3729.156
2	1752	6801.717	968.979	5234.521	8570.319	6760.991
3	1752	10703.284	1233.936	8574.003	12880.665	10704.579
4	1752	16031.253	2043.042	12882.574	20196.854	15808.798
5	1752	34181.015	18580.326	20201.881	245051.61	28356.319

Table 2- Summary Statistics (2017-2020)

Yearly Total Disposable Income (€)						
Income Quintile	Frequency	Mean	SD	Min	Max	Median
1	5279	5901.309	1929.486	307.431	8631.569	6209.757
2	5279	10892.468	1391.331	8632.602	13385.75	10825.686
3	5279	16035.468	1542.126	13385.786	18731.352	16029.453
4	5279	22524.007	2445.748	18732.797	27272.488	22244.684
5	5279	41808.324	18265.814	27275.145	276396.41	36121.625

Moreover, the database includes the lowest household minimum monthly income necessary to face usual expenses, which serves as the closest available proxy to household consumption and thus, may be subject to measurement error. Regarding variable modifications undertaken in this work project, nominal rigidity holds for income, wealth, and consumption components, as all nominal values are converted to 2012 base values, using the Portuguese Consumer Price Index (IPC) constructed by INE, following Fisher et al. (2020)'s methodology. Furthermore, the proxy for consumption is converted to the lowest *yearly* necessary income to pay usual expenses by multiplying the original variable by 12 (months). The impact of total household disposable income on household consumption at a marginal level is therefore the key relationship this work project aims to assess, controlling for other variables.

The role of wealth in consumption

As explained in section II, it is imperative to control for household level of wealth, as the latter is highly positively correlated with household income and affects its consumption decisions. However, unlike other surveys, such as the U.S. PSID, which details information about household net wealth and constructs a joint distribution between income, consumption, and wealth (Fisher et al. 2020), the ICOR does not possess wealth-related stock variables. It solely details the income flows derived from them (received in the income reference period, t-1, reported in t) for each household: capital income, i.e., interests from assets such as bank accounts, certificates of deposit, bonds, treasury bills, dividends and profits from capital investment in an unincorporated business where the person does not work; and income from rental property or land after deducting costs such as mortgage interest payment, maintenance, insurance, among others. It also details the amount of regular taxes paid on wealth.

Thereby, this work project artificially constructs gross wealth variables under the methodology developed in "*An Estimation of U.S family wealth and its distribution from microdata"* (Greenwood 1983). Firstly, gross wealth is divided into 4 categories: (a) financial wealth, (b) housing wealth (i.e., house ownership by owner-occupiers), (c) property wealth (which includes wealth from secondary houses/dwellings and land) and (d) other wealth. Regarding (a), financial wealth is assumed to be equal to the sum of the levels of debt owned (1), deposits owned (2) and stocks owned (3). This subdivision of wealth is based on the OECD aggregate shares regarding households' financial situation. That is, these shares represent the weight of each type of financial assets on total financial assets held by household i, on aggregate. Furthermore, the sum of these three types of assets do not represent 100% of total aggregate financial wealth owned by households. Hence, the macroeconomic representative share is also included when obtaining the individual value of each asset. They are expressed in the following equations:

$$(1)\ DebtOwned_{it} = \frac{(CapitalIncome_{it} * OECD\_share\_of\_debt\_securities_t * sum\_of\_shares_t)}{10year\ Treasury\ bond\ yield_t}$$

$$(2)\ DepositsOwned_{it} = \frac{CapitalIncome_{it} * OECD\_share\_of\_deposits_t * sum\_of\_shares_t}{Average\_deposit\_interest\_rate_t}$$

$$(3)\ EquityOwned_{it} = \frac{CapitalIncome_{it} * OECD\_share\_of\_equity_t * sum\_of\_shares_t}{Average\_return\_stock_t}$$

, where it is assumed that Debt Securities held by households are 10-year Treasury bonds (hence, the use of 10-year Treasury bond yield - (Banco de Portugal 2023)); the average deposit interest rate is equal to the arithmetic average of year interest rates of term deposits of less than 1 year, of between 1-2 years and deposits of longer than two years (Banco de Portugal 2023), and the average return of stock equals the yearly average return of PSI-20, the Portuguese stock market (Investing.com 2023). The numerators of (1), (2) and (3) are therefore debt security income, deposits income and dividends, respectively. The use of average returns is justified by the fact that interest rates do not vary systematically with the income class (Greenwood 1983).

With regards to (b), as there is no real measure of housing wealth by homeowners (i.e., the market value of households' dwelling is not available in ICOR), a lower bound proxy (Krasker and Pratt 1986) measure is used: subjective rent. This is defined as the potential monthly market rent of owner-occupiers' dwellings or of occupiers who pay a reduced rent or to whom accommodation is provided for free. That is, for owner-occupiers, it is the opportunity cost of not renting their home at the market rate. As the goal is measuring housing wealth (which necessarily implies ownership), only owner-occupiers are considered under this measure; the other types of occupiers are attributed a value of 0 in the panel (see Appendix III.1.for detailed methodology). The variable is used as a proxy, due to the fact that rents are strongly correlated to factors that determine housing prices: location, house size, the finishings, etc. and to housing prices themselves, implying that rents probably possess the same sign as the market value of houses (thus, being an appropriate lower bound proxy); in fact, a causal long-term relationship between them can be established (Hargreaves 2008). However, this hypothesis has not been studied for the Portuguese housing market. Although it is not a perfect variable, it is the closest available substitute for housing wealth.

With respect to (c), the latter is constructed as a dummy variable for ownership of a secondary house or land (i.e., it is equal to 1 if the household holds a secondary house or land and 0 otherwise), as it is impossible to obtain the exact value (or even a proxy) of the asset value of a property or land from the income (flow) earned from it. The approach used in (b) is discarded, because computing the market value of a dwelling differs from the determination of the market value of land (as the latter depends on its properties and resources). As the variable used to construct the dummy is "Income from rental of a property or land", this means the latter is not disaggregated, implying that the division between income derived from property and income derived from land is unknown and thus, the estimation of the last asset's worth is impossible.

Lastly, "other wealth" is calculated through the following formula: (4) $OtherWealth_{it} = \frac{Regular\ Taxes\ on\ Wealth}{Tax\ Rate\ on\ Wealth}$. According to the ICOR survey, "Regular taxes on wealth" refers to taxes paid periodically on the ownership or use of buildings or land by owners and paid on other type of assets (such as luxury items). Since the only existing wealth taxes in Portugal are IMI (*Imposto*

Municipal sobre Imóveis), IMT (*Imposto Municipal Sobre as Transmissões Onerosas de Imóveis*) and IS (*Imposto de Selo*) and the last two concern, respectively, taxes on the transferring of property rights and on contracts and titles which are virtually unmeasurable given the available data, only the first one is considered. Assuming IMI for urban buildings, which varies between 0.3% and 0.45% (Portal das Finanças 2023), this study chooses the mid-range tax rate, 0.375% as the Tax Rate on Wealth paid by households. After calculating all types of wealth, under extremely strong assumptions, total wealth is obtained by summing (a), (b) and (d).

The model

After deriving the necessary wealth variables, the estimation model is expressed as a one-way error component model, i.e., a model where the error term is set as $\nu_{it} = c_i + \varepsilon_{it}$.

$$(5)\ lnC_{it} = \boldsymbol{\beta}_1 lnY_{it} + \phi WealthVariables_{it} + \delta DebtVariables_{it} + \vartheta DemographicVariables_{it} + \\ +\eta Time\_Dummies + \pi Poverty\_Dummies_{it} + \nu_{it}$$

Subscript i denotes the cross-section dimension (the household) and t the time-series dimension of the panel. c_i is the time-invariant unobserved household heterogeneity and ε_{it} is the idiosyncratic disturbance, where $\varepsilon_{it} \sim i.i.d\ N(0, \sigma_\varepsilon^2)$. The model is also static, as the relationship between the explanatory variables and the dependent variable is solely contemporaneous. Income and consumption variables are converted into natural logs (see Figures 1 to 4 in Appendix IV.1), in order to normalize their distribution. The key estimator is $\boldsymbol{\beta}_1$ and given the log transformation in both the dependent and income and wealth-related explanatory variables, a contemporaneous increase of 1% in total disposable income - Y_{it}- means, ceteris paribus, on average, a $\boldsymbol{\beta}_1$% increase in C_{it}. This implies that $\boldsymbol{\beta}_1$ represents households' income elasticity of consumption, which is constant across the panel. Debt dummies are included as a lower bound proxy (albeit weak) of debt levels, as to mitigate the effect of gross wealth and the associated potential positive bias on lnY_{it} caused by its absence. The dummy variable "Ability to make ends meet" is included, as it precedes the question in the survey regarding the lowest necessary income to face usual expenses (i.e., the proxy for household consumption) and is correlated with income. The inclusion of this variable is also reinforced by the fact that, in all panels, there are a significant number of households where $C_{it} > Y_{it}$, i.e., the lowest necessary income to face usual expenses exceeds total household disposable income at time t. Moreover, this may reinforce the widely supported economic conclusion that households value consumption smoothing, even in times of deep economic recession. Hence, this variable serves as a "mean shift" between households in the model and due to its correlation with income and consumption, it should also impact the estimation of $\boldsymbol{\beta}_1$.

IV. Methodology

Under an unbalanced fixed-T short-panel (where N, the number of households largely exceeds T, the number of years in the panel), the methodology must account for several theoretical considerations. In an unbalanced panel data setting, given a random draw of household i from the population, $z_i \equiv (z_{i1}, z_{i2}, z_{i3}, z_{i4})$ is a 4×1 vector of selection indicators, where $z_{it} = 1$ if (x_{it}, y_{it}) is observed and 0 if not, for t=1,2,3,4. This implies that the selection indicators tell which time periods are missing for i . Thus, the number of periods observed per household is equal to $T_i \equiv \sum_{t=1}^{4} z_{it}$ (Wooldrigde 2001).

The structural linear unobserved effects regression for each household is defined as:

$$(6)\ lnC_{it} = \alpha + \beta x'_{it} + \eta\ Year' + c_i + \varepsilon_{it},$$

where β is a 1×27 vector of coefficients, x_{it} is a 1×27 vector of explanatory continuous and discrete variables and η is a $1 \times (\mathrm{T} - 1)$ vector set of year dummies (where T=4) (see Appendix III.2 to find the vector form of this equation).

This specification can be estimated through either fixed effects, random effects or a Pooled OLS model, under their respective specific conditions. For consistency, as N→+∞, the following common assumptions to the three estimations must hold (Wooldrigde 2001): (6.1) Linearity in the parameters; (6.2) at a cross-section level, the sample must be random- this necessarily holds in the case of ICOR, as households are randomly selected and possess a design weight (see Appendix II.3 for definition); (6.3) no perfect collinearity between regressors; (6.4) Through the Law of Iterated Expectations, the strict exogeneity assumption implies that the idiosyncratic error is uncorrelated with the explanatory variables and the unobserved household-specific heterogeneity (in this case for the 4 years of each panel): $E(x_{it}\,\varepsilon_{it}) = 0$, $E(c_i\,\varepsilon_{it}) = 0$ for t=1,2,3,4. Hence, for consistency of the estimator, orthogonality of the idiosyncratic error with the regressors and the unobserved time-invariant heterogeneity is required. Assumption (6.2) necessarily implies that c_i is a random variable, as it is randomly drawn from a given distribution once. As the model assumes the existence of unobserved heterogeneity (justified in Section II), the first step of the decision on which model to use lies on choosing between estimators that account for it: the fixed effects (FE) and random effects (RE) estimators (see Appendix III.3 on why the Pooled OLS is discarded).

Choosing the Estimator and Robustness tests

The main difference between the FE and RE estimators is that the unobserved household-specific heterogeneity (c_i) is allowed to correlate with the explanatory variables in the former and not in the latter. In a FE model, while the regressors' slope coefficients remain the same for all households, c_i becomes the household intercept that controls for time-invariant household-specific unobserved characteristics. The within-group estimator takes the mean of all observations within each household and subtracts them from the original specification, i.e., it time-demeans the original regression, thereby wiping out all time-invariant regressors: $lnC_{it} - \overline{lnC_\iota} = \beta(\, x'_{it} - \overline{x'_\iota}) + (c_i - \overline{c_\iota}) + (\varepsilon_{it} - \overline{\varepsilon_\iota})$. As the panel is unbalanced, the time averages are calculated as $\overline{lnC_\iota} = T_i^{-1} \sum_{r=1}^{4} z_{ir}\, lnC_{ir}$, $\overline{x'_\iota} = T_i^{-1} \sum_{r=1}^{4} z_{ir} x_{ir}$ and $\overline{\varepsilon_\iota} = T_i^{-1} \sum_{r=1}^{4} z_{ir} \varepsilon_{ir}$. As initially mentioned, T_i is the number of time periods observed for household i and the within-group estimation is computed with the available periods. As the transformed regressors are a function of the original ones, the previously mentioned orthogonality conditions hold as well in this case.

In typical household survey short-panels, while the FE estimator of β is consistent, the FE estimator of individual effects or intercepts (c_i) is not and it is biased, as the number of these parameters increases as N→+∞ (Lancaster 2000), while T remains fixed. Hence, the FE model does not consistently estimate the time-invariant unobserved heterogeneity but rather aims control it, with the goal of providing consistent estimates of the time-varying variables of interest (in this case, the income elasticity of consumption). After the within-transformation, the model is estimated using standard OLS. To conduct asymptotic inference, homoskedasticity and lack of serial correlation of the idiosyncratic error (ε_{it}) are assumed (check Appendix III.4 for detailed conditions), implying a diagonal variance-covariance matrix. However, if the sample counterpart of the population does not present these characteristics (i.e., there is heteroskedasticity and serial correlation), robust Arellano-White variance estimators must be used (Wooldridge 2001).

A downfall is that the FE estimator also does not allow for the inclusion of time-invariant observables that may have relevant explanatory value to the dependent variable or may even be the variable(s) of interest. Moreover, the variation in the demeaned explanatory variables ($x_{it} - \overline{x_\iota}$) may be smaller than variation in x_{it} (particularly in a small T_i setting), caused by the sluggish behavior of x_{it} (i.e., with small standard deviation). This implies that the impact of the disturbance term may be relatively larger, leading to imprecise estimates (Dougherty 2011). As the FE estimator is heavily sample-dependent, this can lead to high-variance estimates.

A random effects estimator can therefore be a solution to this problem, as it partially pools information across units (Clark and Linzer 2015). The specification is $\widetilde{lnC_{it}} = \alpha + \beta \widetilde{x'_{it}} + \widetilde{v_{it}}$, where $\widetilde{lnC_{it}}$, $\widetilde{x_{it}}$ and $\widetilde{v_{it}}$ are quasi-demeaned variables, constructed as: $\widetilde{lnC_{it}} = lnC_{it} - \lambda_i \overline{lnC_i}$ (analogously for $\widetilde{x_{it}}$ and $\widetilde{v_{it}}$), where $\lambda_i = 1 - [\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T_i \sigma_c^2}]$. Nevertheless, it requires stricter assumptions. While still constant over t=1..,4, c_i must have the same properties as the idiosyncratic error, i.e., $c_i \sim i.i.d\ N(0, \sigma_c^2)$. Its effect is subsumed in the disturbance term ($v_{it} = c_i + \varepsilon_{it}$), meaning that while time-invariant regressors can be included in the estimation, the implied necessary additional orthogonality condition is $E(x_{it}\, c_i\ ) = 0$, for t=1,…,4. Moreover, to assure efficiency of the RE estimator, homoskedasticity must hold both in the idiosyncratic error and on the unobserved effect c_i: $E(\varepsilon_i \varepsilon_i' | x_{it}, z_i, c_i) = E(\varepsilon_i \varepsilon_i') = \sigma_\varepsilon^2 I_T$ and $E({c_i}^2 | x_{it}) = \sigma_c^2$. This implies that Var($v_{it}$)= $\sigma_\varepsilon^2 + \sigma_c^2$. Given the composite error $v_{it} = c_i + \varepsilon_{it}$, even if the idiosyncratic error term is not serially correlated, there will necessarily be serial correlation, through c_i, in each period: $E(v_{it} v_{is}) = E((c_i + \varepsilon_{it})(c_i + \varepsilon_{is})) = E(c_i^2) = \sigma_c^2$. Thus, unlike the FE estimator, the variance-covariance matrix of the RE is not diagonal and serial correlation is not equal to 0, but rather equal to the constant variance of c_i. Since RE is asymptotically equivalent to the GLS estimator, under its standard assumptions, it is more efficient than the FE estimator. Thus, both FE and RE models are deemed to be suitable for estimation purposes, as the random selection process of the sample implies that c_i is random as well. Hence, having established the assumptions for consistency, unbiasedness, and efficiency, one must perform robustness tests to each panel, to check whether these assumptions hold in the sample and consequently, to assert which model to use, so appropriate inference can be conducted.

The modified Wald test for groupwise heteroskedasticity in a FE model is performed, right after estimating the model by fixed effects with regular standard errors. The null hypothesis is $H_0: \sigma^2_{\varepsilon_i} = \sigma^2_{\varepsilon}\ \ for\ all\ i <=> \ H_0: Homoskedasticity$. The null hypothesis shall be rejected in favor of the alternative (of Heteroskedasticity) at a 5% significance level. Then, under the same FE estimation, the test for autocorrelation in panel data is performed, under $H_{0:}$ No first-order correlation (Drukker 2003). As heteroskedasticity and serial correlation are found in the 14 panels, Arellano-White clustered standard errors are hereafter used in the FE model.

The choice between FE and RE essentially lies in whether the unobserved heterogeneity is correlated with the regressors, i.e., whether $E(x_{it}\, c_i\,) = 0$ holds or not. If there are doubts whether c_i is actually correlated with the regressors and given that the RE estimator is relatively more efficient, the Durbin-Wu-Hausman test is computed. All in all, this test compares the FE and RE estimates of the slope parameters: $\widehat{\beta_{FE}}$ and $\widehat{\beta_{RE}}$. Under H_0, both coefficients are consistent, but the RE is more efficient, i.e., $Avar\left(\widehat{\beta_{FE}}\right) - \ Avar\left(\widehat{\beta_{RE}}\right) > 0$. Under the alternative H_a, $\widehat{\beta_{RE}}$ is inconsistent while $\widehat{\beta_{FE}}$ remains consistent. Analogously, H_0: c_i is uncorrelated with x_{it} and H_a: c_i is correlated with x_{it} .

As the homoskedasticity assumption fails, the robust form of the Hausman variable addition test is used (Wooldridge 2001). Using standard OLS on the following regression: $\widetilde{lnC_{\iota t}} = \alpha + \ \beta\, \widetilde{x'_{\iota t}} + \zeta\ddot{w}'_{it} + \ \widetilde{v_{\iota t}}$, where $\widetilde{lnC_{\iota t}}$ and $\widetilde{x_{\iota t}}$ are quasi-time demeaned variables (in this case, x_{it} includes all variables, time-varying, time-invariant and time dummies), where a fraction of the time average is removed from the observation, i.e., $\widetilde{lnC_{\iota t}} = lnC_{it} - \lambda_i \overline{lnC_{\iota}}$ (similarly for $\widetilde{x_{\iota t}}$ and $\widetilde{v_{\iota t}}$) and λ_i is the

GLS weight used in random effects estimation, which is consistently estimated (full methodological and computational derivations are in Appendix III.5). w_{it} is a time-varying subset of x_{it}, solely including only the variables of interest in this particular case (other time-varying and time-invariant control variables and aggregate time dummies are excluded) and $\ddot{w}'_{it}$ is a time-demeaned version of w_{it}. The robust Wald statistic is computed under $H_0: \zeta = 0$. Again, under this hypothesis, both FE and RE estimations are consistent and the random effects model is more efficient. As the null hypothesis of the robust Hausman test is rejected in all panels, RE is deemed inconsistent (due to $E(c_i x_{is}) \neq 0$) and thus, the FE estimator is the most adequate to find the income elasticity of consumption of each panel.

Calculating the Marginal Propensity to Consume

Given that the marginal propensity to consume (MPC) out of total disposable income is defined as the proportional increase in consumption from an additional unit of (disposable) income ($\frac{\partial C}{\partial Y}$), the above-mentioned elasticity must be multiplied by the average propensity to consume (APC), i.e., the share of total income that is consumed rather than saved, $\frac{C}{Y}$ (see proof in Appendix III.6). Following Fisher et al. 2020, for each panel, the MPC out of income is computed by income and wealth quintiles and for the overall panel. The longitudinal and unbalanced nature of the panel must be acknowledged when estimating the constant APC and the APC by income and wealth quintiles, as not doing so implies assuming each observation represents (wrongly) a unique household, ignoring hence household-specific APCs and outliers. Thus, after calculating APC_{it}, the household's mean APC is estimated ($\overline{APC_i}$) and subsequently, the panel's weighted APC is computed, for the whole panel and by income and wealth quintiles (see Appendix III.7 for full methodology).

Furthermore, as concluded in Fisher et al. (2020), the APC is steeper by income quintile than by wealth quintile. This comes as no surprise, as savings are a positive function of income if the savings rate is positive and constant, implying that, in absolute terms, higher-income households save more than their lower-income counterparts. Moreover, it has been empirically shown that the lowest income quintile has the lowest savings rate and highest quintile possesses the highest rate, which further reinforces this result (Bunting 1991). Conversely, the flatter APC distribution by wealth may be explained by wealth's intrinsic relatively lower liquidity level (and subsequently, a weaker direct link to consumption) and by the fact that, in this study, it is calculated as a lower bound proxy, which can underestimate the impact of the financial accelerator and borrowing abilities on C_{it}. The sample's overall APC was only below 1 in the last two panels, 2016-2019 and 2017-2020, suggesting a high average household level of indebtness, a low average negative savings rate or both.

V. Results

After choosing the FE model, over the 14 four-year duration panels, controlling for wealth and debt levels and for household characteristics (such as activity and marital status) , the income elasticities of consumption (β_1) lie between 0.02481% and 0.0915% (see Table 3 for 5 panels; see Appendix IV.3 for all panels). This means that, *ceteris paribus*, on average, if Y_{it} increases by 1%, C_{it} will increase by a specific amount inside that interval, in the sample. These small values imply a highly income inelastic consumption, which in theory may be due to prioritizing consumption smoothing over time, as the change is perceived as transitory. Also, the strong effect of unobserved household heterogeneity on household's reaction to income changes may undermine the statistical power of the FE estimation of β_1, as these time-invariant characteristics are left out. This effect is reinforced in such a short panel, where disposable income variation over the years is low (which is emphasized by a low within R^2). Furthermore, as the proxy of consumption regards solely usual and predictable household spending, sudden unexpected expenses are not included, implying that outliers are not considered, which contributes to a low within variation in C_{it}. Hence, these results may underestimate the true average income elasticity of consumption.

Table 3- Fixed Effects Estimation: 5 of the 14 panels

	2004-2007	2007-2010	2010-2013	2013-2016	2017-2020
lnYit	**.066*** **	**.043*** **	**.056*** **	**.058*** **	**.045*** **
	(.018)	(.015)	(.015)	(.01)	(.01)
ln(FinancialWealth)	-.006	-.001	.002	.001	-.001
	(.004)	(.002)	(.002)	(.001)	(.001)
ln(HousingWealth)	.009*	0	.008*	.013***	.014***
	(.005)	(.002)	(.004)	(.004)	(.004)
ln(OtherWealth)	0	-.001	-.002	.001	.002
	(.002)	(.001)	(.002)	(.001)	(.001)
Ratio of unemployed people in household	-.118***	-.132***	-.141***	-.096***	-.084***
	(.045)	(.038)	(.034)	(.024)	(.028)
Ratio of retired people in household	-.122***	-.093***	-.124***	-.104***	-.017
	(.038)	(.03)	(.035)	(.028)	(.029)
Ratio of other inactive people in household	-.111***	-.101***	-.159***	-.071***	-.003
	(.037)	(.034)	(.035)	(.027)	(.028)
Year 2	.16***	.105***	.011	.02**	.017**
	(.014)	(.013)	(.012)	(.01)	(.008)
Year 3	.234***	.153***	-.053***	-.001	.03***
	(.015)	(.014)	(.013)	(.01)	(.008)
Year 4	.331***	.124***	-.078***	-.018	-.021**
	(.017)	(.016)	(.014)	(.011)	(.01)
Household Size	.105***	.083***	.155***	.136***	.105***
	(.024)	(.023)	(.019)	(.013)	(.013)
Owns (secondary) property wealth	-.021	.032	-.027	.003	.048**
	(.043)	(.036)	(.034)	(.025)	(.022)
Other debt: Heavy Financial Burden	-.021	-.05***	-.037**	-.055***	-.037***
	(.02)	(.016)	(.016)	(.012)	(.01)
Other debt: Slight Financial Burden	.051*	.031	.072***	.063***	.032**
	(.029)	(.022)	(.02)	(.016)	(.016)
Marital status of HH head (=1 if married)	-.003	.012	.023*	.012	.047***
	(.016)	(.012)	(.013)	(.011)	(.01)
Ability to make ends meet (=1 if easy)	-.068***	-.052***	-.087***	-.06***	-.055***
	(.017)	(.015)	(.013)	(.01)	(.009)
Housing debt: Heavy Financial Burden	-.348	.024	-.027	-.039	-.005
	(.327)	(.103)	(.068)	(.093)	(.045)
Housing debt: Slight Financial Burden	.036**	.034***	.034***	.029***	.037***
	(.015)	(.012)	(.01)	(.008)	(.008)
Mean household age	-.003	-.006**	.007**	.002	.002

	(.003)	(.003)	(.003)	(.002)	(.002)
_cons	8.172***	9.057***	8.21***	8.252***	8.166***
	(.282)	(.231)	(.229)	(.153)	(.151)
Observations	8394	9969	12587	18774	23206
R-squared (within)	.167	.054	.053	.051	.034
Clusters (Households)	3,204	3,769	4,603	7,004	8,271

The dependent variable is lnC_t.
*Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1*

After estimating the weighted APC and the APCs across income and wealth quintiles, the marginal propensities to consume are computed. The constant MPC obtained for the whole sample is significantly lower than the ones obtained in other literature: across the 14 panels, the constant MPCs lies between 2.795% and 9.129%, below the 10% obtained in Fisher et al. (2020). When estimating the MPC by income quintile, on average, the latter strictly decreases with the level of income (shown in Tables 4 and 5; see Appendix IV.4 for the other tables); regarding wealth, the relationship is not as linear: in some cases, the distribution is U-shaped (namely in panel 2012-2015, displayed in Table 5) , a result that was also found in Pistaferri and Saporta-Eksten (2012), or presents a greater MPC in the middle wealth tiers (such as in panels 2005-2008, shown in Table 4) . Nevertheless, across all panels, the MPC of the bottom wealth quintile is always higher than the MPC of the top wealth quintile.

	Table 4 (2006-2009)		Table 5 (2012-2015)	
Quintile	MPC		MPC	
	MPC (Income Quintile)	MPC (Wealth Quintile)	MPC (Income Quintile)	MPC (Wealth Quintile)
1	.1017	.0654	.0688	.0522
2	.0584	.0686	.0447	.0511
3	.0553	.0557	.0391	.0395
4	.0411	.0486	.0331	.0342
5	.0285	.0477	.0271	.0359

Estimating the Aggregate Expenditure Multiplier and Consumption Growth

If MPC heterogeneity indeed exists, it is assumed there is scope for redistributive fiscal policy to boost aggregate demand and subsequently increase national income (Jappelli and Pistaferri 2014). To assess if this theory holds, two scenarios are considered: the first assumes households have the same MPC, regardless of their income and wealth levels - this is the sample's average MPC; the second scenario is of MPC heterogeneity, caused by income and wealth inequality (i.e., there is no independence between the level of income and wealth and propensities to consume).

The impact of MPC heterogeneity and subsequently of income and wealth inequality on aggregate consumption can be determined by comparing the textbook Keynesian aggregate expenditure multiplier (AM) under constant MPC across households (7) $AM_{Homogeneity} = (\frac{1}{(1-mpc)})$ with the multiplier obtained with heterogeneous MPCs: (8) $AM_{Heterogeneity} = ShareQ_1 \frac{1}{(1-mpc_{Q1})} + ShareQ_2 \frac{1}{(1-mpc_{Q2})} + ShareQ_3 \frac{1}{(+1-mpc_{Q3})} + ShareQ_4 \frac{1}{(1-mpc_{Q4})} + ShareQ_4 \frac{1}{(1-mpc_{Q5})})$ (Fisher et al. 2020). The multiplier represents the impact of a change in autonomous aggregate consumption in real national income (Smithies 1948). However, this approach implies some strong assumptions: the real interest rate and prices of goods are fixed, government spending and taxes are equal to 0, and so are imports and exports. The latter assumption is particularly defiant of the Portuguese reality: in 2021, the Trade-to-GDP ratio ($\frac{(Exports+Imports)}{GDP}$) was 86.17%,while the U.S's was 25.48% (The World Bank 2023). Moreover, as reflected by the mentioned authors, this aggregate multiplier does not incorporate behavioral responses (such as wealth and income effects and changes in risk aversion levels) and it is merely indicative of how the impact of an equal transfer to households differs with different MPC assumptions. Hence, as a comparative measure, the methodology undertaken by Jappelli and Pistaferri (2014) is also employed: the government transfers 1% of total national disposable income equally to all individuals in the bottom and top income quintiles, under the two scenarios of homogenous and heterogenous MPCs. General equilibrium effects and distortions are ignored, as this is a lump-sum transfer. Also, the government finances its policies by issuing debt rather than raising taxes from other tiers (see Appendix III.8 for detailed methodology).

Regarding the first procedure, when analyzing the 14 panels, all of them, except the 2006-2009 panel (and the 2007-2010 panel, when estimating the MPCs by wealth quintiles), display a larger multiplier in the presence of MPC heterogeneity across income quintiles than when MPC is presumed constant (see table A32 in Appendix IV.5) ; hence, this implies that an equal lump-sum transfer to all income (wealth) quintiles results, in most cases, in a larger estimated impact when MPC heterogeneity is recognized (J. D. Fisher et al. 2020). Also, as expected, the differences in multipliers are greater between income quintiles than between wealth quintile. Concerning the second approach, the results are even more compelling: in the majority of cases, the impact of targeted transfer to the bottom quintile on aggregate consumption growth is, in some cases, almost double under MPC heterogeneity than in the homogenous scenario (shown below in Table 6); furthermore, the effect of a transfer to the top quintile on aggregate consumption growth under MPC heterogeneity is significantly lower than a transfer to the bottom quintile in both scenarios,

Table 6 – Aggregate Consumption Growth (Jappelli and Pistaferri 2014)

Years (Panels)	MPC scenarios		
	Homogenous	Heterogenous	
	Transfer to Q1	Transfer to Q1	Transfer to Q5
2004-2007	0.043%	0.083%	0.015%
2005-2008	0.026%	0.051%	0.009%
2007-2010	0.027%	0.044%	0.012%
2010-2013	0.044%	0.076%	0.023%
2012-2015	0.032%	0.053%	0.021%
2013-2016	0.066%	0.113%	0.036%
2017-2020	0.071%	0.133%	0.033%

which reinforces the conclusion that widening inequality deeply affects aggregate consumption growth, i.e., inequality has a double negative impact on the latter.

VI. Limitations and conclusion

Using household survey panel data across 14 succesive panels, this work project concludes that the Portuguese MPCs out of total disposable income by income and wealth levels are aligned with the extensive (mainly U.S.) literature on this topic: MPC heterogeneity exists across both income and wealth quintiles, with the former being more evident than the latter. The link between the MPCs, income and wealth distributions and aggregate consumption is the same as the one found in Fisher et al. (2020) and Jappelli and Pistaferri (2014): the aggregate multipliers are greater when MPC heterogeneity is recognized than when MPCs are assumed homogenous across income and wealth distribution; aggregate consumption grows significantly more with a targeted transfer to the bottom income quintile under MPC heterogeneity (i.e., assuming the lowest income quintile has the highest MPC) than when assuming a constant income-independent MPC; moreover, this work project shows that a transfer to the top income quintile generates an aggregate consumption growth notably smaller than a transfer to the bottom tier, in both MPC scenarios. This latter result shows that even when agents possess the same MPC, widening the gap between the richest and the poor implies a relatively lower aggregate demand growth, which entails short-run low output growth.

However, the interpretation of these conclusions must be conducted carefully, as there are several inherent limitations. From a methodological and data-related perspective, both C_{it} and wealth variables are proxies, with the wealth components being artificially calculated, under strong assumptions. The only wealth variable that presents some consistent statistical significance throughout the panels is the housing wealth proxy, i.e., the subjective rent of owner-occupiers homes. Indeed, unlike PSID, which displays detailed information on consumption, income, wealth and debt values for each household, the ICOR does not present information regarding the last two components, meaning there is no available individual or household balance sheet data. Besides providing potential useful information regarding households' net worth, this data could help construct risk and preference profiles, enriching thereby the information about consumption preferences. Hence, this is a major drawback of the survey, that most likely affects the estimation of the variable of interest. Moreover, even though a proxy for wealth is created, it is impossible to construct a proxy for household debt, implying that net worth may be overstated. Lastly, the panel's short size may post a problem in estimating the model through FE (even though it is the most appropriate linear approach given the robustness tests results), due to low household (within) variation, which may strenghten the bias. Hence, for future research, longer panels and the inclusion of net worth and detailed consumption variables are suggested. Given that household specific-effects play an important role, this work project also supports interacting income variables with household (or group) observed effects in future work, as accounting for these effects is much more realistic than assuming a constant income elasticity of consumption across households and groups.

Regarding aggregate multiplier estimations, these values are calculated under strong assumptions: the simple Keynesian multiplier excludes endogenous behavioral effects and assumes a closed economy scenario. Moreover, Jappelli & Pistaferri (2014)'s method employed in this study disregards the government's budget constraint and the long-term effects of constant deficit financing. Hence, this work project only aims to study the mechanisms of inequality and aggregate demand and thus, policy inferences cannot and should not be conducted.

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Appendix

I: Definitions and Equations:

1. C= a+cY_d , where a is autonomous consumption, c is the aggregate marginal propensity to consume (0<c<1) and Y_d is disposable income.
2. In According to Gelman (2020), cash-on-hand represents the sum of liquidity preferences (i.e., the sum of checking and savings accounts) from the previous period plus the disposable income received in current period. Thus, it is the total income available to household to consume. In this thesis, given that information on savings and checking accounts of individuals and households is not available, cash-on-hand is equivalent as household total disposable income, or current income.
3. Full model

$$lnC_{it} = \alpha + \boldsymbol{\beta}_1 lnY_{it} + \beta_2 lnFinancialWealth + \beta_3 lnHousingWealth_{it} + \beta_4 lnOtherWealth_{it} + \beta_5 owns\_property\_land\_wealth_{it} + \beta_6 ratio\_unemployed\_members\_per\_hh_{it} + \beta_7 ratio\_retired\_member\_per\_hh_{it} + \beta_8 ratio\_other\_inactive\_members_{it} + \beta_9 hh\_size_{it} + \beta_{10} Ability\_to\_make\_ends\_meet_{it} + \beta_{11} Average\_hh\_age + \delta Housing\_Debt\_Dummies_{it} + \theta Other\_Debt\_Dummies_{it} + \emptyset Marital\_status\_of\_HH\_head_{it} + \eta Time\_Dummies + \pi Poverty\_Dummies_{it} + v_{it}$$

II. Survey Data: ICOR/EU-SILC

1. Variables (ICOR/EU-SILC Code in parenthesis) :
   a. Y_t -Total disposable household income (HY020):
      i. $\text{Total disposable household income}_{i,t-1} = \sum_{j=1}^{N}(\text{Gross employee cash or near cash income}_{j,t-1} + \text{Company car}_{j,t-1} + \text{Gross cash benefits or losses from self employment}_{j,t-1} +$

$\text{Pensions received from individual private plan}_{j,t-1} + \text{Unemployment benefits}_{j,t-1} +$

$\text{Old age benefits}_{j,t-1} + \text{Survivor benefits}_{j,t-1} + \text{Sickness benefits}_{j,t-1} +$

$\text{Education related allowances}_{jt}\big)_{i,t-1} +$

$\text{Income from rental of a property or land}_{i,t-1} + \text{Family/}$

$\text{children related allowances}_{i,t-1} + \text{Social exclusion not elsewhere classified}_{i,t-1} +$

$\text{Housing allowances}_{i,t-1} + \text{Regular inter household cash transfers received}_{i,t-1} +$

$\text{Interests, dividends, profit from capital investments in unincorporated business}_{i,t-1} +$

$\text{Income received by people aged under } 16_{i,t-1} - \text{Regular taxes on wealth}_{i,t-1} -$

$\text{Regular inter household cash transfer paid}_{i,t-1} -$

$\text{Tax on income and social insurance contributions}_{i,t-1},$ where $N =$

$Total\ number\ of\ people\ living\ in\ household\ in\ year\ t$

ii. Reference period: t-1

iii. Unit: All household members

2. Panel Structure: the panel displays the following longitudinal construction: the sample for any one year (i.e., cross-sectionally speaking) consists of four replications/subsample, which have been in the overall sample for 1 to 4 years; any replication lasts 4 years in the survey and each year (except in year 1 of collection, where the first three replications do no last 4 years), one replication from the previous year is dropped and a new one is added: see figure below. This implies that, under a successive panel structure, from year t to year t+1, the sample overlap corresponds to 75%, the overlap between t and t+2 is 50% and t and t+3 is 25%. Hence, this aspect and the fact that, by construction, only 25% of sampled households are present in the panel for the 4 years (meaning that only 25% of the total sample is balanced) must be acknowledged when estimating the parameters of interest. Since some observations are dropped under the previously mentioned conditions, less than

25% of sampled households are present in the panel for 4 years, reinforcing the unbalanced nature of the panel.

3. Design weight: According to the 2009 ICOR Methodological guidelines (page 14), it can be defined as the inverse of the household's probability of selection.

III. Methodology

1. Calculation of Housing Wealth
    a. $Annual\ Subjective\ Rent_{it} = Montlhy\ Subjective\ Rent * 12 * IPC_{2012}$
    b. $Annual\ Subjective\ Rent\ of\ OwnerOccupiers_{it} = Annual\ Subjective\ Rent_{it} * OwnerOccupier_{it}$, where $OwnerOccupier_{it}$= 1 if occupier owns the dwelling; $OwnerOcuppier_{it}$=0 if occupier pays reduced or no rent on the dwelling
2. In vector form, it can be displayed as: $lnC = X\beta + \eta Year + Z_c c + \varepsilon$, where lnC is $N\sum_{i=1}^{N} T_i \times 1$, X is $N\sum_{i=1}^{N} T_i \times 27$, , ε is $N\sum_{i=1}^{N} T_i \times 1$ and lastly, $Z_c = I_N \otimes \iota_{Nt}$, where I_N is the identity matrix of dimension N, ι_{Nt} is a vector of ones of dimension $N\sum_{i=1}^{N} T_i$ and $\otimes$ denotes the Kronecker product. Z_c can either represent a selection matrix of ones and zeros or if c_i is assumed to be time-invariant across periods, it represents the matrix of individual dummies (Batalgi 2021).
3. Choosing between Pooled OLS, FE and RE Estimation: Why not Pooled OLS?
    a. Pooled OLS could provide consistent estimators under certain assumptions; however, the estimation of the model through this method ignores the time component of each household, i.e., it disregards that the same household i has (repeated) observations over t=1,…4 and thereby, the time-dependence in observations for the household i. Under its standard assumptions, it treats each observation (it) as a regular cross-section unit, meaning that under t=1,…4, i1, i2 i3

and i4 would be mutually independent and identically distributed. Thus, it disregards the existence of potential heterogeneity within each household, implying omitted variable bias and endogeneity, if $E(x_{it}\, c_i\ ) \neq 0$ if systematic time-invariant unobserved (or even observed) heterogeneity indeed exists. Also, even if $E(x_{it}\, c_i\ ) = 0$ (which is a fundamental assumption of the Pooled OLS model), implying that c_i is considered as part of the error term, the composite errors ($\nu_{it} = c_i + \varepsilon_{it}$) are serially correlated, as c_i is present in each point in time. This means that ν_{it} is not weakly dependent (Wooldrigde 2001), further contributing to a biased and inefficient estimation. Hence, only large N and fixed-T asymptotics could estimate consistent coefficients when applying Pooled OLS.

4. Homoskedasticity and lack of serial correlation assumptions: Given that the orthogonality condition holds, $E\left(\varepsilon_i\varepsilon_i{}'|\, x'_{is}, z_i, c_i\right) = E(\varepsilon_i\varepsilon_i') = \sigma_\varepsilon^2 I_{T_i}$, where $\sigma_\varepsilon^2 I_{T_i}$ is the variance-covariance matrix. The first equality $E\left(\varepsilon_i\varepsilon_i{}'|\, x'_{is}, z_i, c_i\right) = E(\varepsilon_i\varepsilon_i')$ implies that heteroskedasticity is ruled out (as the conditional and unconditional variance matrices are equal), σ_ε^2 denotes the constant unconditional variance of the idiosyncratic error for household i,across t and I_T represents serially uncorrelated idiosyncratic errors (as I_T is a diagonal matrix) .
5. Robust Hausman Variable Test: (Wooldridge, 10. Basic Linear Unobserved Effects Panel Data Models 2001)
    a. Run the random effects model with Robust Arellano-White standard errors (in Stata, it is the cluster (by household) standard errors are robust to both heteroskedasticity and autocorrelation in the idiosyncratic error.

b. Construct $\widehat{\sigma_c^2}$ and $\widehat{\sigma_\varepsilon^2}$: first, retrieve the scalars $\widehat{\sigma_c}$ and $\widehat{\sigma_\varepsilon}$ obtained from the regression (in Stata language, this means obtaining the scalars from the "e matrix", i.e., the matrix with stored values. Secondly, square them.

c. Create $\widehat{\lambda_\iota} = 1 - [\frac{\widehat{\sigma_\varepsilon^2}}{\widehat{\sigma_\varepsilon^2}+T_i\widehat{\sigma_c^2}}]$, where $T_i \equiv \sum_{t=1}^{4} z_{it}$.

d. Time-demean time-varying variables, i.e., $\ddot{x_{it}} = (\, x'_{it} - \overline{x'_\iota})$. This is constructed manually in Stata, by computing the time-average for each household and then subtracting it from the observation, where: $\overline{x'_\iota} = T_i^{-1}\sum_{r=1}^{4} z_{ir}x_{ir}$ and $\overline{\varepsilon_\iota} = T_i^{-1}\sum_{r=1}^{4} z_{ir}\varepsilon_{ir}$.

e. Quasi-demean the dependent and independent variables: $\widetilde{lnC_{\iota t}}$, $\widetilde{x'_{\iota t}}$ and $\widetilde{v_{\iota t}}$ are quasi-demeaned variables, constructed as: $\widetilde{lnC_{\iota t}} = lnC_{it} - \widehat{\lambda_\iota}\overline{lnC_\iota}$ (similarly for $\widetilde{x'_{\iota t}}$ and $\widetilde{v_{\iota t}}$.

f. Construct manually the quasi-demeaned equation and estimated it by pooled OLS: $\widetilde{lnC_{\iota t}} = \hat{\alpha} + \beta\,\widetilde{x'_{\iota t}} + \widetilde{v_{\iota t}}$. $\hat{\alpha} = 1 - \widehat{\lambda_\iota}$ is a time-demeaned constant (in Stata, include this new constant on the right-hand side of the equation and use the *nocons* option). When comparing with the Stata's econometric package for random effects estimation (i.e., *xtreg, re cluster (Household)*). If they are identical or extremely close to rounding differences, then the manually constructed equation is consistently estimated.

g. Following the estimation of $\widetilde{lnC_{\iota t}} = \alpha + \beta\,\widetilde{x'_{\iota t}} + \zeta\ddot{w}'_{it} + \widetilde{v_{\iota t}}$, where $\ddot{w}'_{it}$ is a subset of $\ddot{x}'_{it}$,

h. The robust Wald statistic is computed under $H_0: \zeta = 0$ and rejected if the p-value of the test statistic is 5%.

6. Estimation of the Marginal Propensity to Consume:

   a. Algebraically, Average Income Elasticity of Consumption= $\beta_1 = \frac{\%\Delta C_t}{\%\Delta Y_t} = \frac{\frac{\partial C_t}{C_t} * 100\%}{\frac{\partial Y_t}{Y_t} * 100\%} <=> \beta_1 = \frac{\partial C_t}{\partial Y_t} * \frac{Y_t}{C_t} <=> \frac{\partial C_t}{\partial Y_t} = \beta_1 * \frac{C_t}{Y_t}$

7. Given the longitudinal component of the panel, the overall average propensity to consume of the panel and the APC by income and wealth quintiles are calculated through the following procedure: concerning the first, the latter is calculated firstly for each observation ($APC_{it} = \frac{C_{it}}{Y_{it}}$, for i=1,…N) and subsequently, as the household's (time) average APC: $\overline{APC_i} = \frac{\sum_{t=1}^{T_i} APC_{it}}{T_i}$, where t=1…,$T_i$. It is crucial to estimate the households' time mean APC, as households are the units of study; not doing so would imply the assumption that each observation represents (wrongly) a unique household, ignoring thereby household-specific APCs. Secondly, in order to compute the overall APC, since the panel is unbalanced, one must compute the following weighted average: $APC = \frac{\sum_{i=1}^{N} T_i \overline{APC_i}}{\sum_{i=1}^{N} T_i}$, where the numerator is the weighted sum of all household time-mean APCs adjusting for/multiplying by their frequency in the panel (T_i) and the denominator represents the total number of observations in the panel. The same process applies to the estimation of APC by income and wealth quintiles, except that now the number of households and subsequently observations differ by quintile (i.e., $APC^{Quintile} = \frac{\sum_{i=1}^{N_{Quintile}} T_i \overline{APC_i}}{N_{Quintile} T_i}$) and that household's time-average APC is sorted according to income and wealth levels.

8.

   a. $G = 0.01 \times \sum_i y_i$ → Government transfer

b. $Net\ transfer\ received\ by\ household\ i\ in\ debt\ experiment\ k$: $\tau_i(k) = \frac{G}{n^k}\mathbf{1}\{i \in g^k\}$→ $\mathbf{1}\{i \in g^k\}$ is an indicator on whether i is a transfer recipient or not; n^k is the total number of transfer recipients.

IV. Tables, Graphs and Results

1. Figure A1- Total Disposable Income 2009-2012 (Levels)

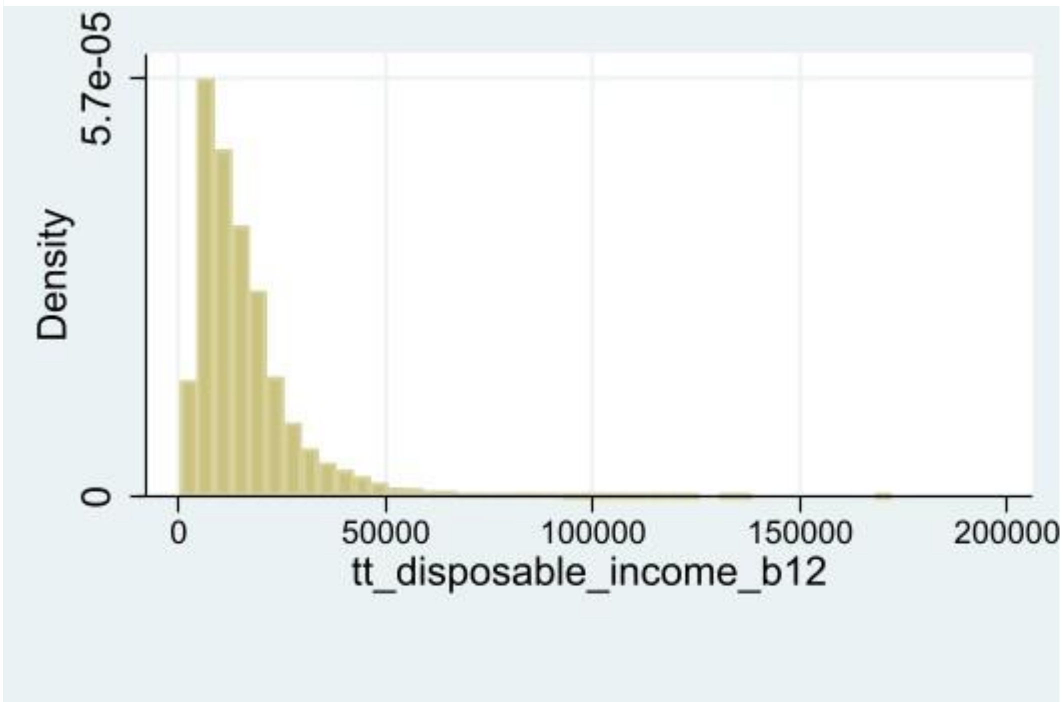


Figure A2- Total Disposable Income 2009-2012 (Logarithms)

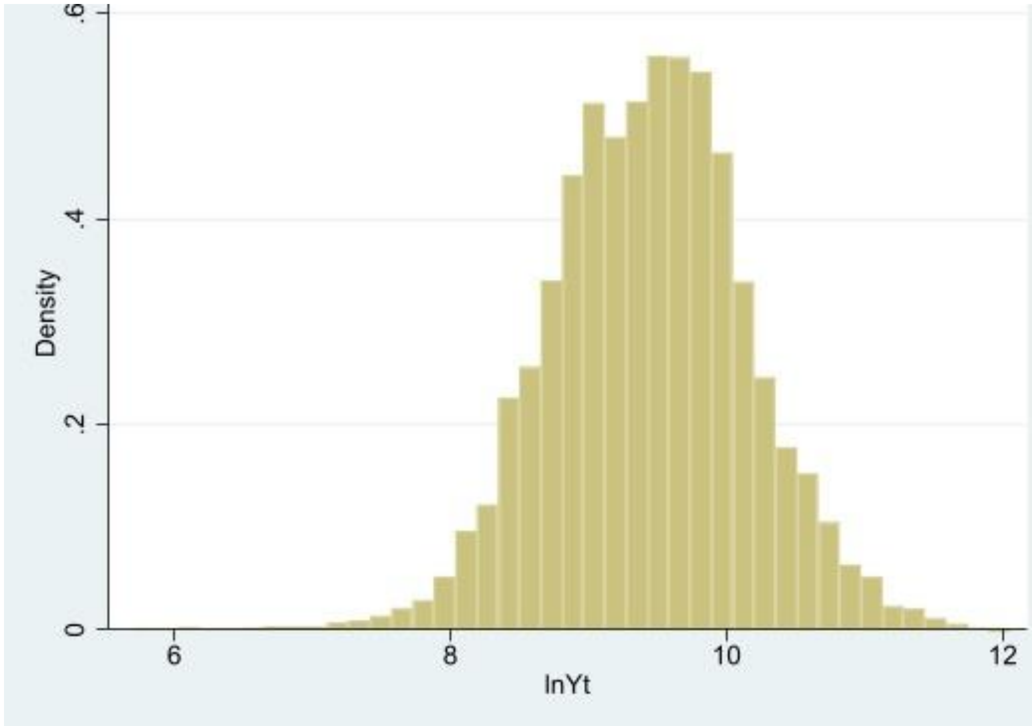


Figure A3- Consumption 2009-2012 (Levels)

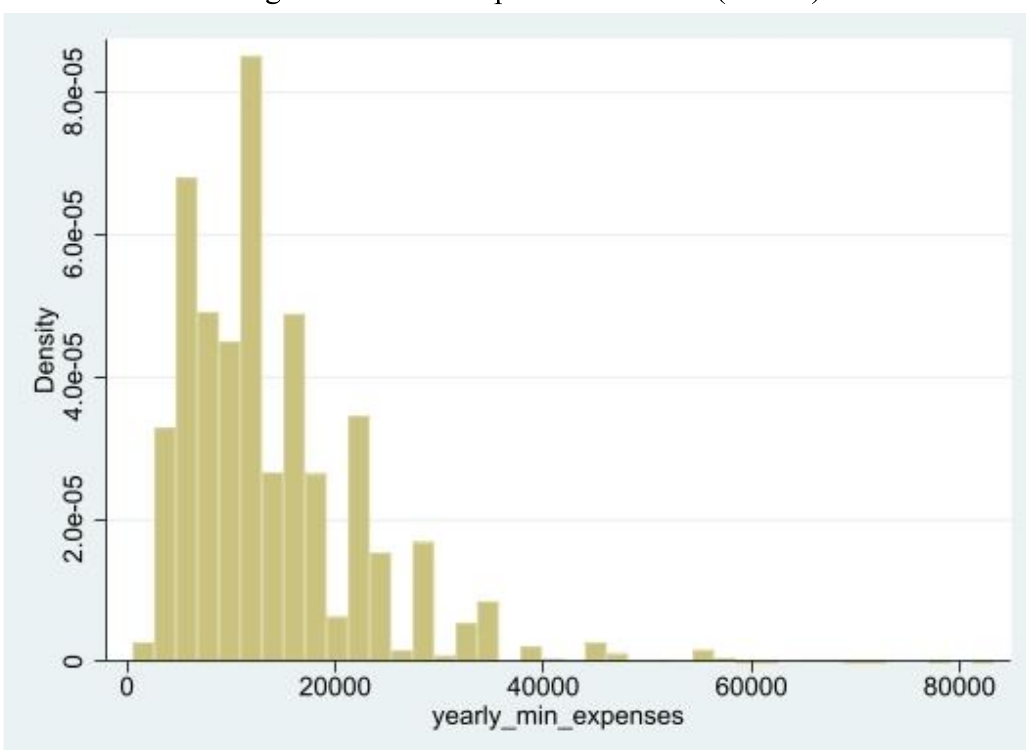
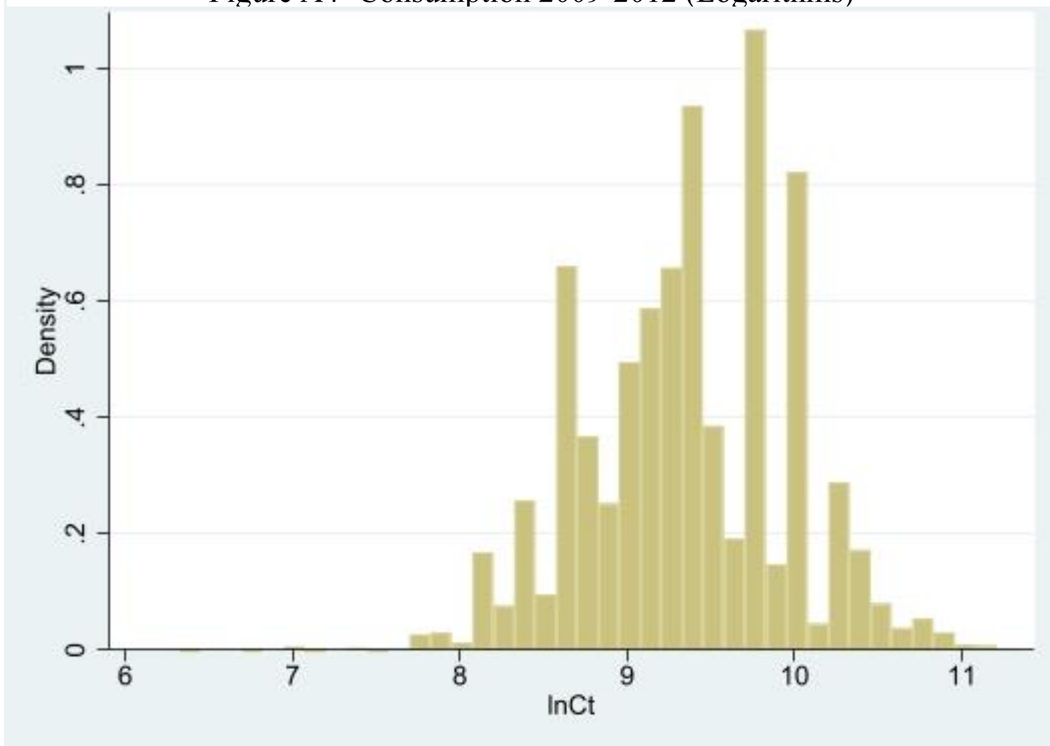


Figure A4- Consumption 2009-2012 (Logarithms)



2. Descriptive and Summary Statistics

   a. Yearly Household Total Disposable Income

Table A1-Yearly Household Total Disposable Income (€)- Summary Statistics

	Mean	SD	Min	Max	Median
2004-2007	14248.38	13686.74	31.163	245051.61	10704.579
2005-2008	15237.67	14404.102	31.163	251103.06	11461.529
2006-2009	15620.93	15015.682	172.284	318968.72	12078.774
2007-2010	15980.23	14110.563	249.255	318968.72	12465.708
2008-2011	15969.74	13637.419	302.643	276100.97	12343.958
2009-2012	16201.72	13280.795	302.643	172037.83	12728.963
2010-2013	16433.71	13413.245	291.906	243159.72	13042.055
2011-2014	16678.80	13418.296	291.906	243159.72	13491.963

2012-2015	16687.99	13849.366	291.906	326868.09	13518
2013-2016	17036.99	14350.237	303.988	384058.41	13721.494
2014-2017	17411.86	15322.197	303.282	487177.19	14061.937
2015-2018	17768.96	14698.378	303.282	384058.41	14437.118
2016-2019	18437.39	14671.169	307.431	383556	15130.738
2017-2020	19431.47	15002.132	307.431	276396.41	16028.732

Table A2- Yearly Total Disposable Income (€)- Summary Statistics (2004-2007)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	3524.615	1164.785	31.163	5233.704	3729.156	Left
2	6801.717	968.979	5234.521	8570.319	6760.991	Right
3	10703.284	1233.936	8574.003	12880.665	10704.579	Normal
4	16031.253	2043.042	12882.574	20196.854	15808.798	(right)
5	34181.015	18580.326	20201.881	245051.61	28356.319	(right)

Table A3- Yearly Total Disposable Income (€)- Summary Statistics (2005-2008)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	3896.331	1265.174	31.163	5716.494	4123.119	-.617
2	7346.582	1034.783	5716.986	9274.747	7258.319	.188
3	11520.736	1300.537	9279.216	13876.285	11461.529	.044
4	17232.582	2184.887	13879.925	21566.525	16952.556	.321
5	36192.131	19508.372	21575.418	251103.06	30178.183	4.32

Table A4- Yearly Total Disposable Income (€)- Summary Statistics (2006-2009)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	4155.4	1307.731	172.284	6059.232	4378.776	-.595
2	7835.086	1073.112	6060.467	9810.571	7796.702	.114
3	12085.423	1332.319	9811.808	14520.692	12079.384	.047
4	17742.051	2132.365	14527.439	22019.043	17482.152	.302
5	36297.691	21956.095	22021.516	318968.72	30298.577	5.721

Table A5-Yearly Total Disposable Income (€)- Summary Statistics (2007-2010)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	4539.32	1323.532	249.255	6480.18	4718.034	-.558
2	8262.682	1073.536	6480.877	10229.731	8208.128	.112
3	12499.266	1327.331	10232.534	14871.824	12465.793	.07

4	18203.238	2168.744	14872.226	22492.146	17998.531	.273
5	36408.196	19014.6	22495.980	318968.72	30894.324	5.154

Table A6-Yearly Total Disposable Income (€)- Summary Statistics (2008-2011)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	4755.072	1304.426	302.643	6649.703	4901.085	-.623
2	8282.819	993.644	6649.897	10109.075	8248.655	.107
3	12390.546	1331.344	10115.338	14790.458	12344.374	.079
4	18037.374	2123.241	14793.986	22300.15	17888.074	.269
5	36390.286	17383.856	22312.904	276100.97	30898.259	3.468

Table A7-Yearly Total Disposable Income (€)- Summary Statistics (2009-2012)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	4908.978	1430.351	302.643	6884.846	5129.364	-.71
2	8595.689	1018.278	6884.857	10491.102	8570.514	.07
3	12786.2	1349.292	10491.208	15245.517	12729.861	.104
4	18413.989	1984.161	15253.014	22334.348	18302.688	.199
5	36309.522	16337.612	22335.678	172037.83	30728.088	2.467

Table A8-Yearly Total Disposable Income (€)- Summary Statistics (2010-2013)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	4947.526	1474.792	291.906	6960	5254.308	-.84
2	8762.331	1092.477	6962.931	10758	8723.795	.069
3	13114.886	1389.253	10760.000	15595.555	13042.419	.081
4	18849.132	2085.716	15598.991	22989.828	18646.631	.263
5	36500.502	16722.753	22990.307	243159.72	31595.916	3.719

Table A9-Yearly Total Disposable Income (€)- Summary Statistics (2011-2014)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	4959.714	1580.226	291.906	7156	5273.729	-.778
2	9084.297	1154.911	7156.957	11190.579	9039.701	.103
3	13534.575	1351.004	11193.488	15970.787	13492.034	.031
4	19286.472	2109.251	15971.457	23328	19122	.214
5	36534.017	16862.061	23328.746	243159.72	31444.563	3.777

Table A10-Yearly Total Disposable Income (€)- Summary Statistics (2012-2015)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	4921.149	1595.508	291.906	7193.712	5223.687	-.756
2	9055.104	1120.192	7195.422	11083.124	8989.641	.097
3	13534.892	1401.337	11086.494	16035.842	13518.548	.008
4	19302.31	2105.375	16036.320	23333.73	19064.094	.237

5	36631.427	18377.137	23333.805	326868.09	31069.764	4.937

Table A11-Yearly Total Disposable Income (€)- Summary Statistics (2013-2016)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	4921.66	1643.925	303.988	7199.712	5182.692	-.696
2	9075.082	1139.858	7200.000	11199.552	8989.641	.125
3	13714.929	1467.268	11200.000	16329.992	13721.727	.034
4	19824.86	2236.597	16331.347	23999.041	19579.553	.211
5	37657.591	19091.025	24000.000	384058.41	31930.396	5.942

Table A12-Yearly Total Disposable Income (€)- Summary Statistics (2014-2017)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	5028.494	1663.23	303.282	7319.479	5264.385	-.73
2	9286.899	1202.519	7319.587	11507.09	9214.632	.124
3	14044.91	1499.731	11509.323	16708.816	14064.292	.02
4	20045.378	2188.947	16709.826	24295.027	19794.094	.26
5	38660.806	21765.778	24296.789	487177.19	32603.982	7.227

Table A13-Yearly Total Disposable Income (€)- Summary Statistics (2015-2018)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	5235.58	1729.189	303.282	7641.2	5533.758	-.727
2	9679.388	1231.036	7642.706	11923.025	9642.346	.109
3	14471.659	1492.32	11923.199	17089.768	14437.275	.03
4	20480.298	2220.748	17091.457	24840.402	20279.501	.258
5	38980.454	19440.691	24840.438	384058.41	33200.908	5.372

Table A14-Yearly Total Disposable Income (€)- Summary Statistics (2016-2019)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	5478.721	1796.559	307.431	8030.907	5809.9	-.715
2	10221.286	1324.103	8031.123	12593.394	10145.224	.103
3	15144.369	1486.254	12596.165	17716.723	15130.738	.013
4	21287.257	2358.061	17717.488	25974.533	21003.797	.285
5	40057.443	18484.378	25977.498	383556	34441.496	4.736

Table A15-Yearly Total Disposable Income (€)- Summary Statistics (2017-2020)

Income Quintile	Mean	SD	Min	Max	Median	Skewness
1	5901.309	1929.486	307.431	8631.569	6209.757	-.682
2	10892.468	1391.331	8632.602	13385.75	10825.686	.1
3	16035.468	1542.126	13385.786	18731.352	16029.453	.01
4	22524.007	2445.748	18732.797	27272.488	22244.684	.241
5	41808.324	18265.814	27275.145	276396.41	36121.625	3.38

3. Regression analysis

Table A16- Fixed effects estimation

Variables	2005-2008	2006-2009	2007-2010	2008-2011	2009-2012	2010-2013
lnYt	**.042*** **	**.045*** **	**.043*** **	**.083*** **	**.092*** **	**.056*** **
	(.042)	(.015)	(.015)	(.016)	(.017)	(.015)
ln(FinancialWealth)	.0056227**	.002	-.001	-.005**	-.004	.002
	(.003)	(.002)	(.002)	(.002)	(.002)	(.002)
ln(HousingWealth)	.0026852	.004	0	-.001	.005	.008*
	(.004)	(.004)	(.002)	(.002)	(.003)	(.004)
ln(OtherWealth)	-.0013013	-.002	-.001	.002	-.002	-.002
	(.002)	(.001)	(.001)	(.002)	(.001)	(.002)
Ratio of unemployed people in household	-.0194303	-.075*	-.132***	-.162***	-.12***	-.141***
	(.0406517)	(.043)	(.038)	(.043)	(.04)	(.034)
Ratio of retired people in household	-.0138919	-.041	-.093***	-.061*	-.088**	-.124***
	(.0395282)	(.031)	(.03)	(.036)	(.035)	(.035)
Ratio of other inactive people in household	-.0344823	-.055	-.101***	-.108***	-.12***	-.159***
	(.036)	(.034)	(.039)	(.036)	(.035)	(.035)
Year 2	.0767445***	.092***	.105***	.035***	-.037***	.011
	(.0140216)	(.012)	(.013)	(.012)	(.011)	(.012)
Year 3	.17669***	.181***	.153***	.004	-.034***	-.053***
	(.0151358)	(.014)	(.014)	(.013)	(.013)	(.013)
Year 4	.2582376***	.233***	.124***	.01	-.087***	-.078***
	(.0174007)	(.016)	(.016)	(.015)	(.014)	(.014)
Household size	.1307747***	.112***	.083***	.102***	.138***	.155***
	(.0279248)	(.025)	(.023)	(.023)	(.02)	(.019)
Owns (secondary) property wealth or land	.0039604	.052	.032	-.029	-.029	-.027
	(.0400834)	(.037)	(.036)	(.045)	(.042)	(.034)
Repayment of HHs Other Debt: Heavy Financial Burden	-.0316861	-.057***	-.05***	-.037**	-.027*	-.037**
	(.017)	(.016)	(.016)	(.016)	(.016)	(.016)
Repayment of HHs Other Debt: Slight Financial Burden	.024639	.014	.031	.025	.035	.072***
	(.0258353)	(.024)	(.022)	(.022)	(.022)	(.02)
Marital status of HH head (=1 if married)	.032187**	.039***	.012	-.001	-.001	.023*
	(.0150542)	(.014)	(.012)	(.014)	(.014)	(.013)
Ability to make ends meet (=1 if easy)	-.0707484***	-.078***	-.052***	-.087***	-.089***	-.087***
	(.017378)	(.016)	(.015)	(.015)	(.014)	(.013)
Repayment of HHs Housing Debt: Heavy Financial Burden	-1.251672***	.103	.024	.1	-.064	-.027
	(.0259205)	(.201)	(.103)	(.215)	(.098)	(.068)
Repayment of HHs Housing debt: Slight Financial Burden	.0213224	.018	.034***	.026**	.056***	.034***
	(.013253)	(.013)	(.012)	(.012)	(.011)	(.01)

Mean household Age	-.0021727	-.002	-.006**	-.006**	.001	.007**
	(.0033402)	(.003)	(.003)	(.003)	(.003)	(.003)
_cons	8.512637	8.614***	9.057***	8.791***	8.271***	8.21***
		(.249)	(.231)	(.248)	(.236)	(.229)
Observations	8306	8816	9969	10706	12025	12587
R-squared (within)	0.1398	.113	.054	.047	.057	.053
R-squared (Overall)						

*Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1*

Table A16- Fixed effects estimation

Variables	2011-2014	2012-2015	2013-2016	2014-2017	2015-2018	2016-2019	2017-2020
lnYt	**.025***	**.038*****	**.058*****	**.042*****	**.038*****	**.045*****	**.045*****
	(.013)	(.012)	(.01)	(.009)	(.009)	(.009)	(.01)
ln(FinancialWealth)	.001	.002	.001	.002**	0	-.001	-.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
ln(HousingWealth)	.015***	.014***	.013***	.011***	.011***	.005	.014***
	(.004)	(.004)	(.004)	(.004)	(.003)	(.003)	(.004)
ln(OtherWealth)	-.002*	.001	.001	.001	.002**	.001	.002
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Ratio of unemployed people in household	-.142***	-.078***	-.096***	-.099***	-.143***	-.13***	-.084***
	(.029)	(.027)	(.024)	(.023)	(.021)	(.021)	(.028)
Ratio of retired people in household	-.087***	-.103***	-.104***	-.052*	-.041	-.043*	-.017
	(.032)	(.033)	(.028)	(.029)	(.025)	(.025)	(.029)
Ratio of other inactive people in household	-.119***	-.069**	-.071***	-.097***	-.1***	-.102***	-.003
	(.031)	(.032)	(.027)	(.028)	(.023)	(.023)	(.028)
Year 2	-.059***	-.001	.02**	-.012	-.013*	-.01	.017**
	(.011)	(.01)	(.01)	(.009)	(.007)	(.007)	(.008)
Year 3	-.079***	.017	-.001	-.025**	-.017**	0	.03***
	(.012)	(.011)	(.01)	(.01)	(.008)	(.008)	(.008)
Year 4	-.063***	.005	-.018	-.027**	-.006	.011	-.021**
	(.013)	(.012)	(.011)	(.011)	(.008)	(.008)	(.01)
Household size	.138***	.128***	.136***	.114***	.129***	.128***	.105***
	(.015)	(.015)	(.013)	(.012)	(.011)	(.011)	(.013)
Owns (secondary) property wealth or land	-.004	-.003	.003	.021	.03	.027	.048**
	(.029)	(.028)	(.025)	(.023)	(.02)	(.019)	(.022)
Repayment of HHs Other Debt: Heavy Financial Burden	-.028**	-.041***	-.055***	-.062***	-.05***	-.04***	-.037***
	(.013)	(.013)	(.012)	(.01)	(.009)	(.008)	(.01)
Repayment of HHs Other Debt: Slight Financial Burden	.05***	.07***	.063***	.03**	.029**	.02	.032**
	(.017)	(.018)	(.016)	(.015)	(.014)	(.013)	(.016)

Marital status of HH head (=1 if married)	.037***	.017	.012	.041***	.009	.019**	.047***
	(.012)	(.012)	(.011)	(.009)	(.008)	(.008)	(.01)
Ability to make ends meet (=1 if easy)	-.066***	-.073***	-.06***	-.046***	-.051***	-.053***	-.055***
	(.012)	(.011)	(.01)	(.009)	(.008)	(.007)	(.009)
Repayment of HHs Housing Debt: Heavy Financial Burden	.062	-.013	-.039	-.025	-.043	-.072	-.005
	(.09)	(.122)	(.093)	(.083)	(.074)	(.087)	(.045)
Repayment of HHs Housing debt: Slight Financial Burden	.048***	.041***	.029***	.029***	.033***	.031***	.037***
	(.009)	(.009)	(.008)	(.007)	(.006)	(.007)	(.008)
Mean Household Age	.002	.002	.002	-.001	.001	.002*	.002
	(.002)	(.002)	(.002)	(.002)	(.001)	(.001)	(.002)
_cons	8.703***	8.447***	8.252***	8.561***	8.391***	8.327***	8.166***
	(.177)	(.162)	(.153)	(.142)	(.136)	(.124)	(.151)
Observations	14321	14909	18774	23579	30022	29659	23206
R-squared(within)	0.0504	0.0432	0.0512	0.0408	0.0392	0.0360	0.0339
R-squared (Overall)							

4. MPCs

Table A17- MPC by Income and Wealth Distributions (2004-2007)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.1776112	.1146027
2	.0959289	.0970955
3	.0833886	.082503
4	.0604712	.093392
5	.0390265	.0667977

Table A18- MPC by Income and Wealth Distributions (2005-2008)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.1072737	.0670398
2	.0529912	.0647348
3	.0519905	.0527093
4	.0356208	.0492132
5	.0241869	.0378054

Table A19- MPC by Income and Wealth Distributions (2006-2009)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.1016903	.0654414
2	.0583572	.0685658
3	.0552558	.0547268
4	.0411133	.0486079
5	.0285003	.0476532

Table A20- MPC by Income and Wealth Distributions (2007-2010)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.0830126	.0664941
2	.0557473	.0494992
3	.0497729	.0497684
4	.0389605	.047889
5	.0282122	.0419145

Table A21- MPC by Income and Wealth Distributions (2008-2011)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.1539641	.1186218
2	.1020827	.0890999
3	.0980012	.0946309
4	.0760652	.0989472
5	.0563604	.0849129

Table A22- MPC by Income and Wealth Distributions (2009-2012)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.1750445	.0960978
2	.1087103	.1305886
3	.1013245	.1107148
4	.0809104	.101909
5	.0610066	.0872622

Table A23- MPC by Income and Wealth Distributions (2010-2013)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.1092533	.0741936
2	.0653126	.0711957
3	.0591243	.0668627
4	.0484297	.0549139
5	.0353738	.0501532

Table A24- MPC by Income and Wealth Distributions (2011-2014)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.0462711	.0335911
2	.0289781	.0342463
3	.0257078	.0281278
4	.0217053	.0222846
5	.0170916	.0215063

Table A25- MPC by Income and Wealth Distributions (2012-2015)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.0688248	.0522152
2	.0447374	.0511175
3	.0391365	.0394877
4	.0330937	.034214
5	.0270965	.0358562

Table A26- MPC by Income and Wealth Distributions (2013-2016)

Quintile	MPC	
	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.1064548	.0721398
2	.0645648	.0758509
3	.0576621	.0593258
4	.0492733	.0553511
5	.0363186	.0516524

Table A27- MPC by Income and Wealth Distributions (2014-2017)

	MPC	
Quintile	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.0789271	.0506879
2	.0467985	.0475828
3	.0397951	.0463116
4	.0330441	.0429491
5	.0242401	.0352566

Table A28- MPC by Income and Wealth Distributions (2015-2018)

	MPC	
Quintile	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.0706677	.0424061
2	.0408415	.0416099
3	.0340139	.0429368
4	.029657	.0379481
5	.0216967	.0319562

Table A29- MPC by Income and Wealth Distributions (2016-2019)

	MPC	
Quintile	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.0807297	.0485774
2	.0449319	.0440959
3	.0386649	.0483786
4	.0329716	.0435446
5	.0248866	.0375915

Table A30- MPC by Income and Wealth Distributions (2017-2020)

	MPC	
Quintile	MPC(Income Quintile)	MPC(Wealth Quintile)
1	.0752764	.0484846
2	.0407665	.0407823
3	.0347849	.0399793
4	.0282412	.0382667
5	.0229209	.0329738
6	.0429096	

5. Aggregate multiplier and consumption growth

Table A31 – Aggregate Consumption Growth (Jappelli and Pistaferri 2014)

Years (Panels)	MPC		
	Homogenous	Heterogenous	
	Transfer to bottom quintile	Transfer to bottom quintile	Transfer to top quintile
2004-2007	0.0426%	0.08284%	0.0147%
2005-2008	0.02597%	0.0512%	0.00872%
2006-2009	0.02769%	0.04941%	0.01066%
2007-2010	0.02713%	0.04403%	0.01216%
2008-2011	0.05518%	0.08732%	0.02796%
2009-2012	0.06876%	0.11433%	0.03566%
2010-2013	0.04413%	0.07594%	0.02254%
2011-2014	0.02071%	0.03428%	0.0127%
2012-2015	0.03239%	0.05326%	0.02093%
2013-2016	0.06665%	0.11286%	0.03606%
2014-2017	0.06208%	0.10995%	0.03013%
2015-2018	0.06865%	0.12305%	0.03255%
2016-2019	0.08112%	0.14736%	0.03826%
2017-2020	0.07142%	0.13308%	0.03303%

Table A32- Aggregate Keynesian Multiplier

Period	Constant	Income Quintile	Wealth Quintiles
2004-2007	1.1005	1.1036	1.1007
2005-2008	1.0574	1.0585	1.0577
2006-2009	1.0604	1.0599	1.0577
2007-2010	1.0539	1.0541	1.0538
2008-2011	1.1078	1.1091	1.1079
2009-2012	1.1176	1.1198	1.1180
2010-2013	1.0677	1.0684	1.0678
2011-2014	1.0288	1.0289	1.0288
2012-2015	1.0444	1.0447	1.0445
2013-2016	1.0671	1.0679	1.0673
2014-2017	1.0466	1.0469	1.0466
2015-2018	1.0409	1.0413	1.0410
2016-2019	1.0465	1.0469	1.0465
2017-2020	1.0421	1.0425	1.0421